Neural interaction measures

Andrea Brovelli

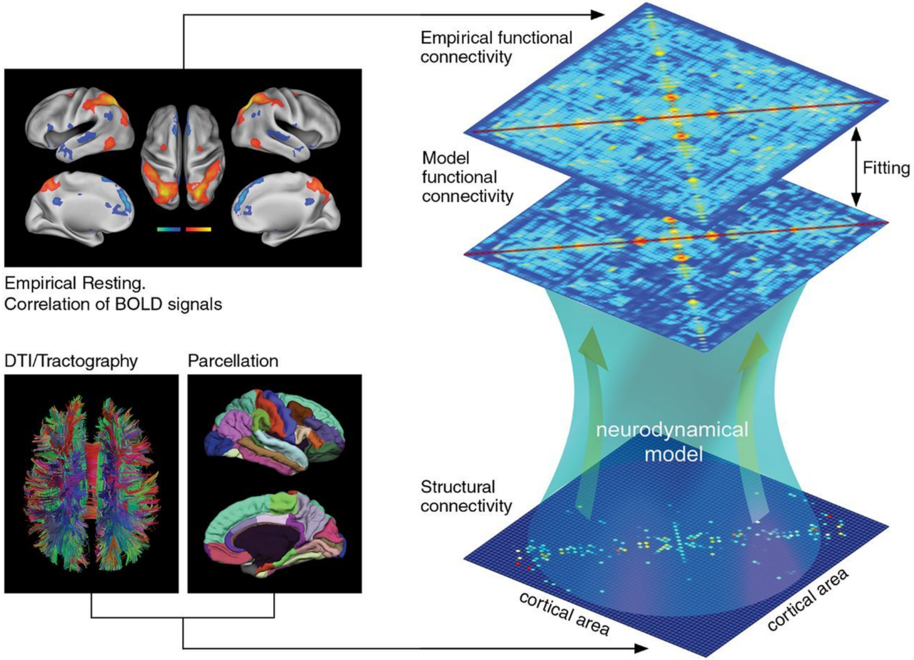
BraiNets Team

Institutions

Funding

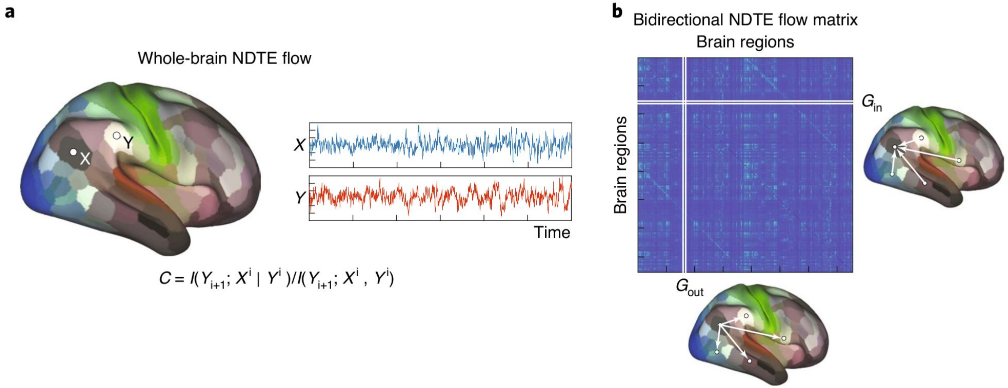
EBRAINS

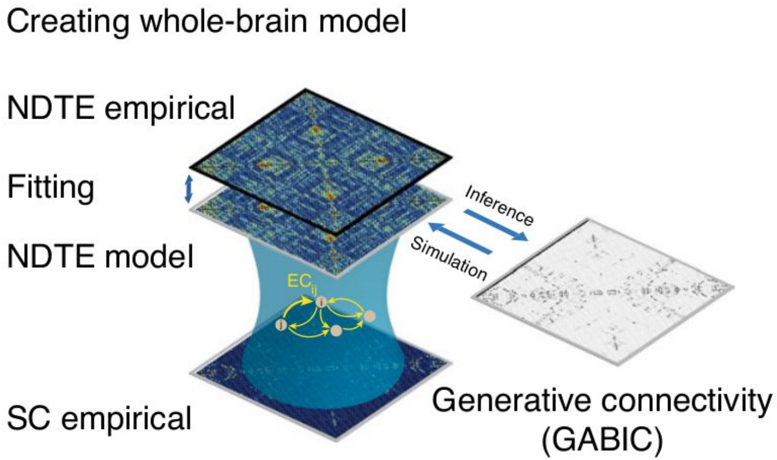
Brain models and neural interaction measures



Deco et al (2013) *JNeurosci*

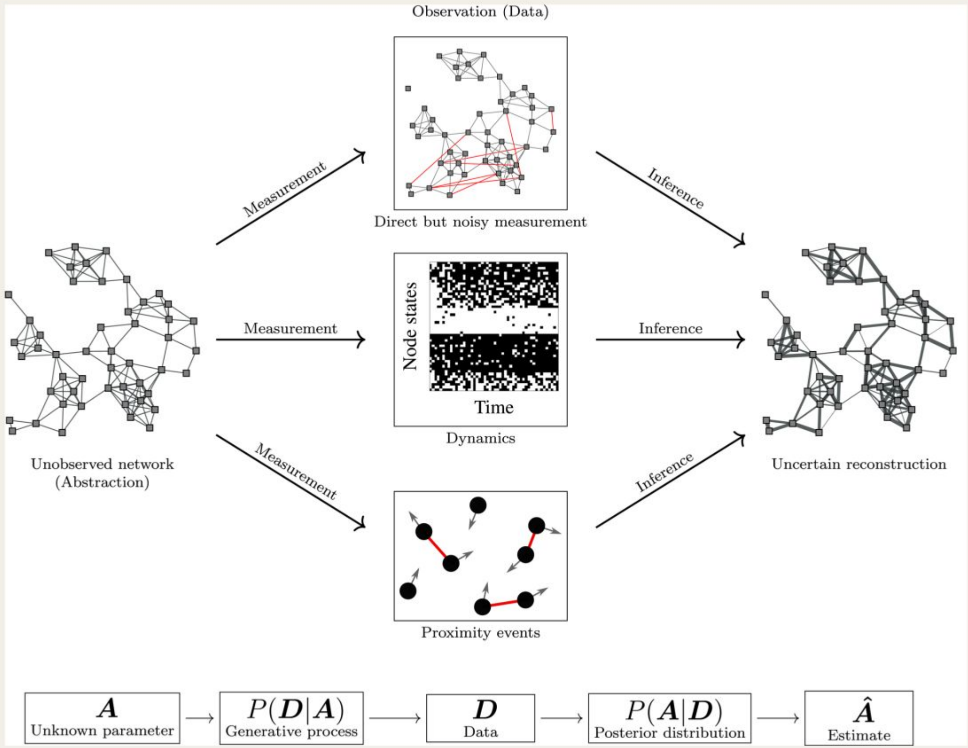
Brain models and neural interaction measures





Deco et al (2021) *Nature Human Behaviour*

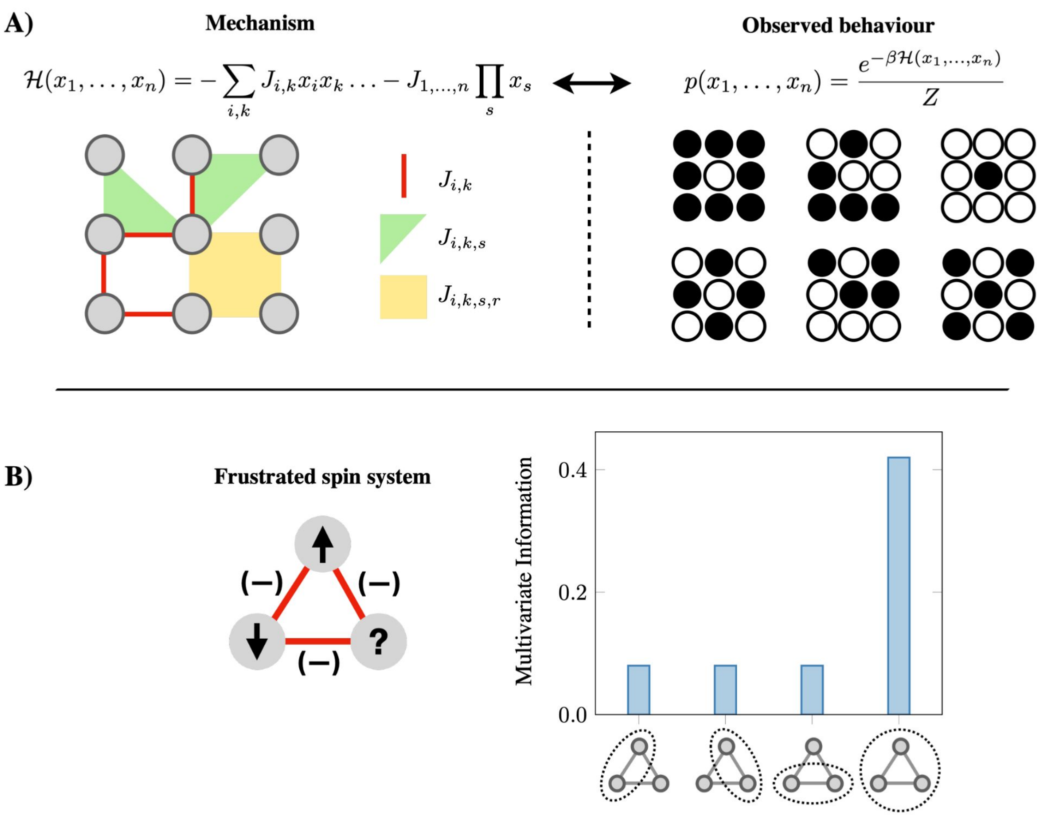
Linking data and theory in network science



A network of interactions $\boldsymbol{A}$ that gives as a result some kind of observational data $\boldsymbol{D}$ should not in general be conflated with the data itself. Instead, we need to recognize that the data $\boldsymbol{D}$ is the result of measurement process $P(\boldsymbol{D}|\boldsymbol{A})$ that is conditioned on the unseen network, but is to some extent unavoidably decoupled from it. In order to estimate the underlying network, we need to perform an inferential step $P(\boldsymbol{A}|\boldsymbol{D})$, which needs to include our modeling assumptions about how the network and the data are generated. The resulting estimate $\hat{\boldsymbol{A}}$ will have an uncertainty that reflects the experimental design, accuracy of the measurements and overall feasibility of the particular reconstruction problem.

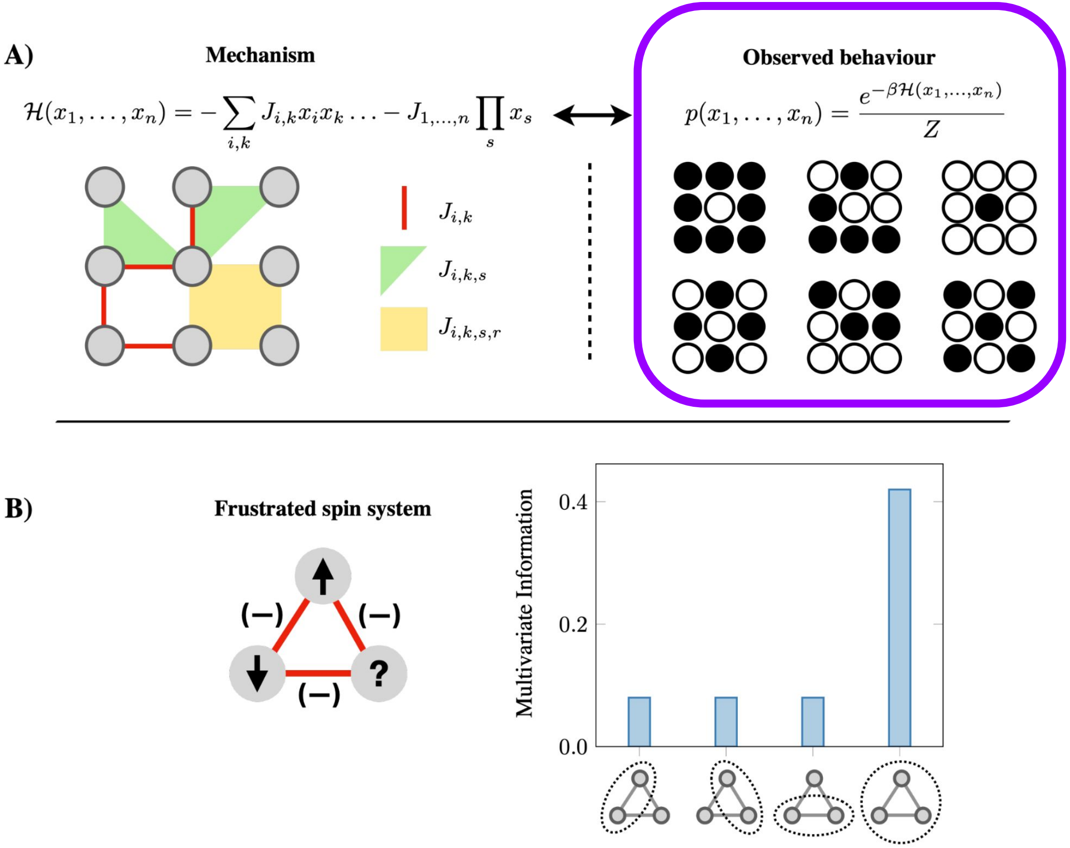
Peel et al (2022) *Nat Commun*

Linking "Mechanisms" and "Behaviours"



Rosas et al. (2022) *Nature Physics*

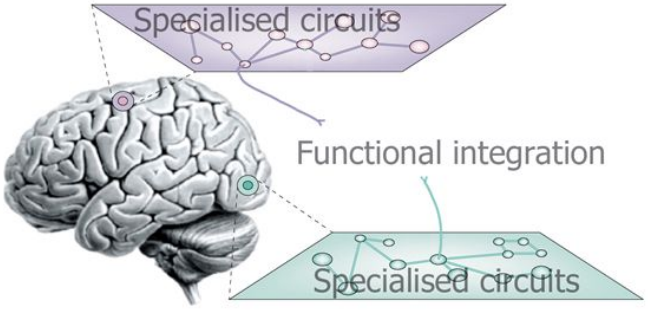
Linking "Mechanisms" and "Behaviours"



Rosas et al. (2022) *Nature Physics*

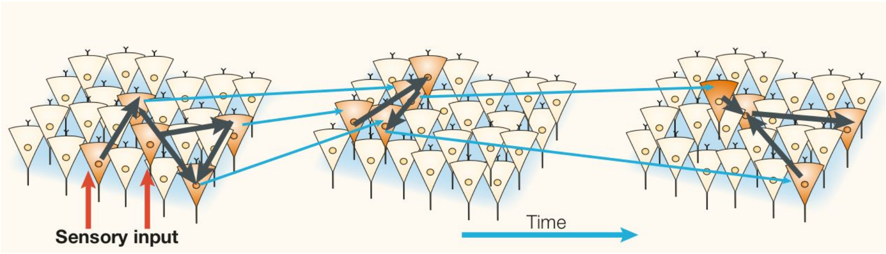
Collective behaviours and neural interactions across scales

The brainweb hypothesis



Varela et al (2001) *Nature Reviews Neurosci*

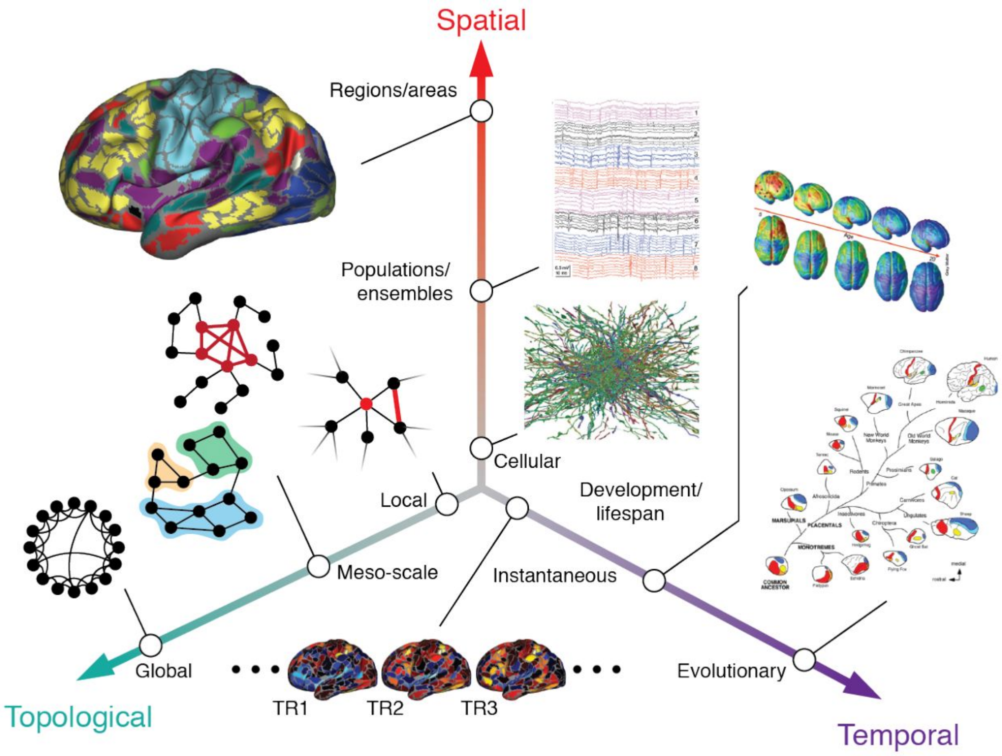
Cell assembly hypothesis (Hebb 1949)



Harris (2005) *Nature Reviews Neurosci*

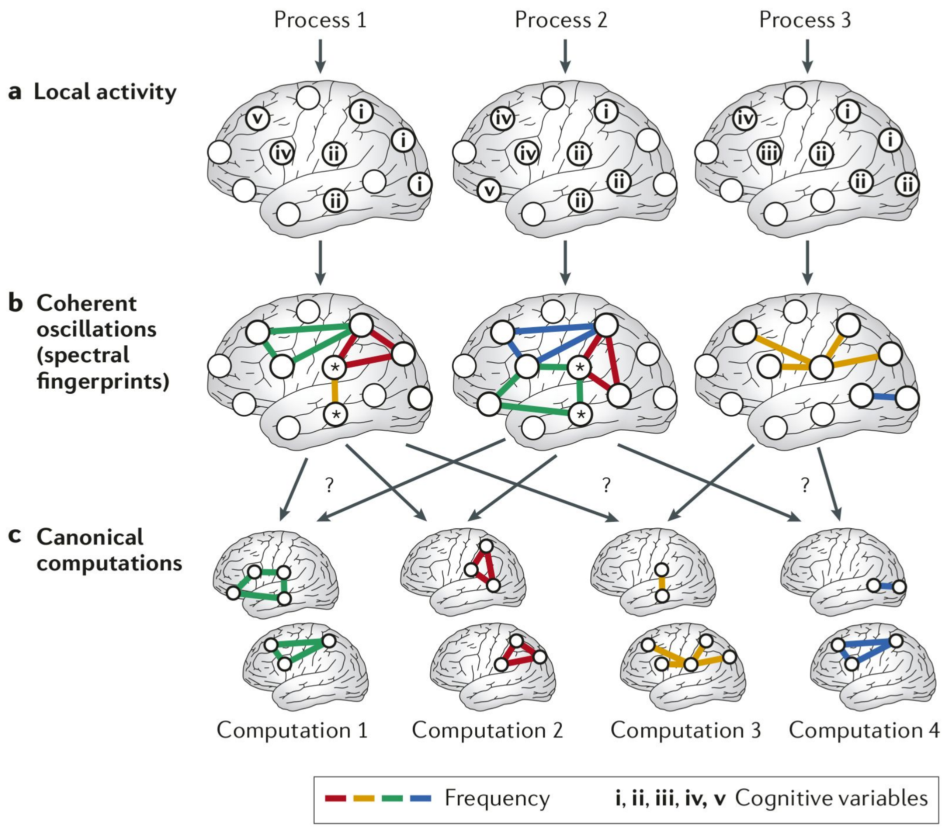

Q1. Interaction Rules
"Do as your neighbours"
Q2. Functional Role
Foraging, defense and travel

Neural interactions are complex



Betzel and Bassett (2016) *Neuroimage*

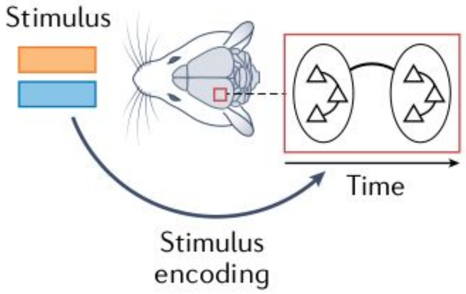
Neural oscillations and brain communication



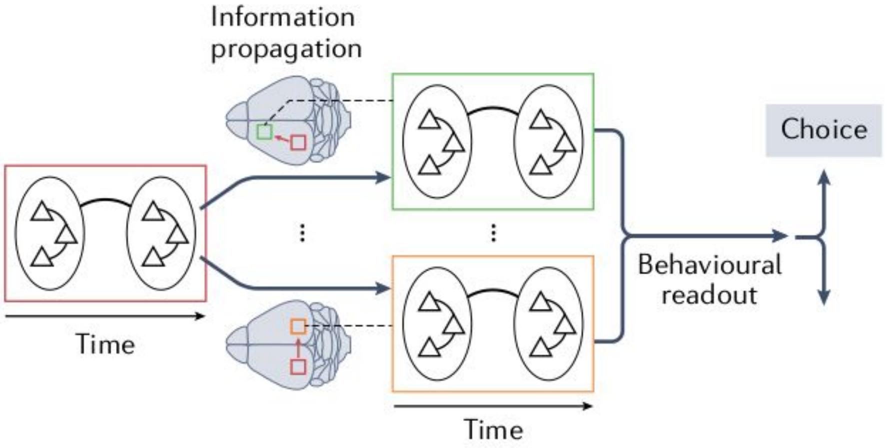
Siegel et al. (2012). Spectral fingerprints of large-scale neuronal interactions. *Nature Rev Neurosci*

Why study neural interactions?

<u>Distributed encoding</u> of information relevant for cognition

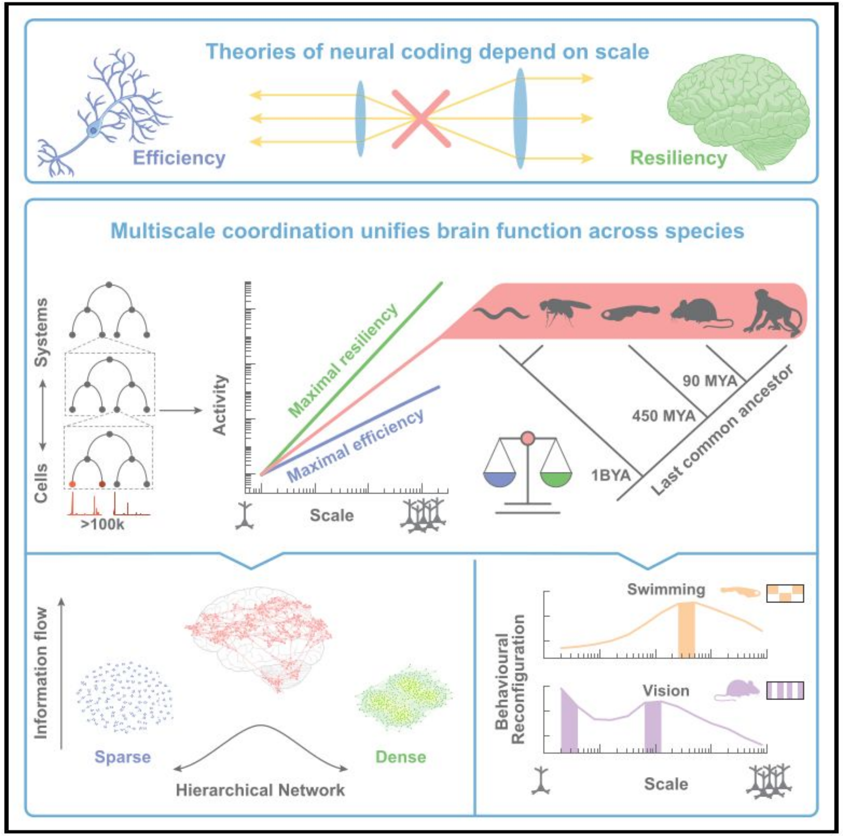


<u>Broadcasting</u> of information relevant for cognition



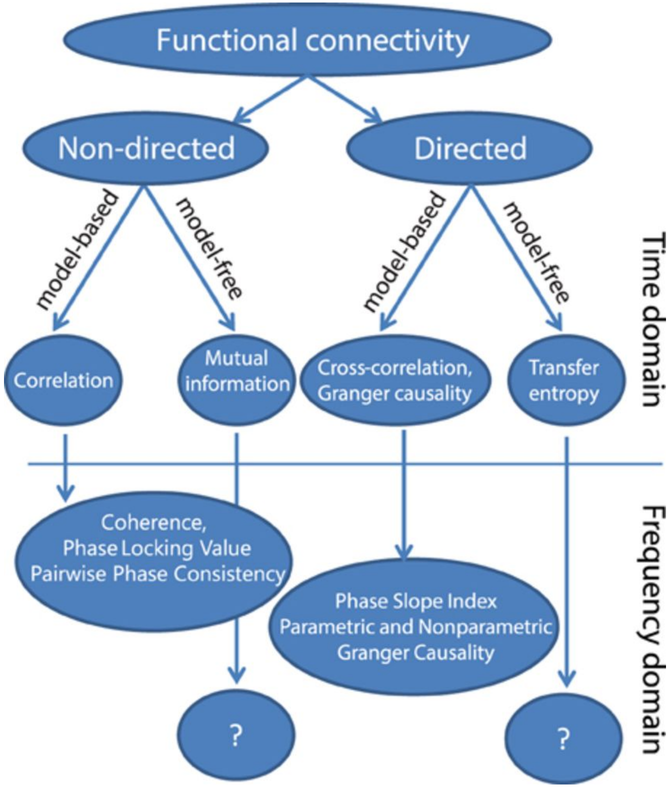
Panzeri et al (2022) *Nature Reviews Neurosci*

Efficient encoding across scales



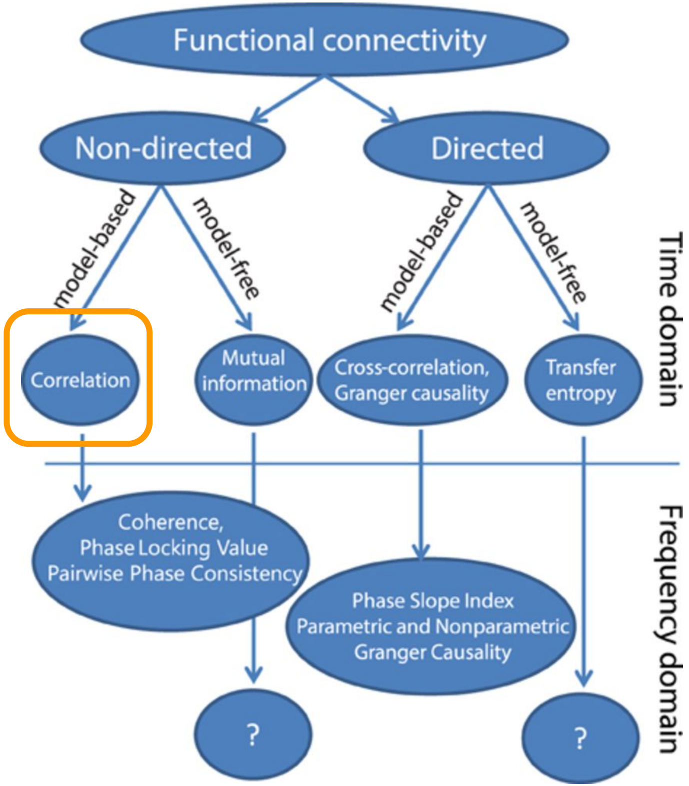
Munn et al. (2024) *Cell*

Functional Connectivity measures



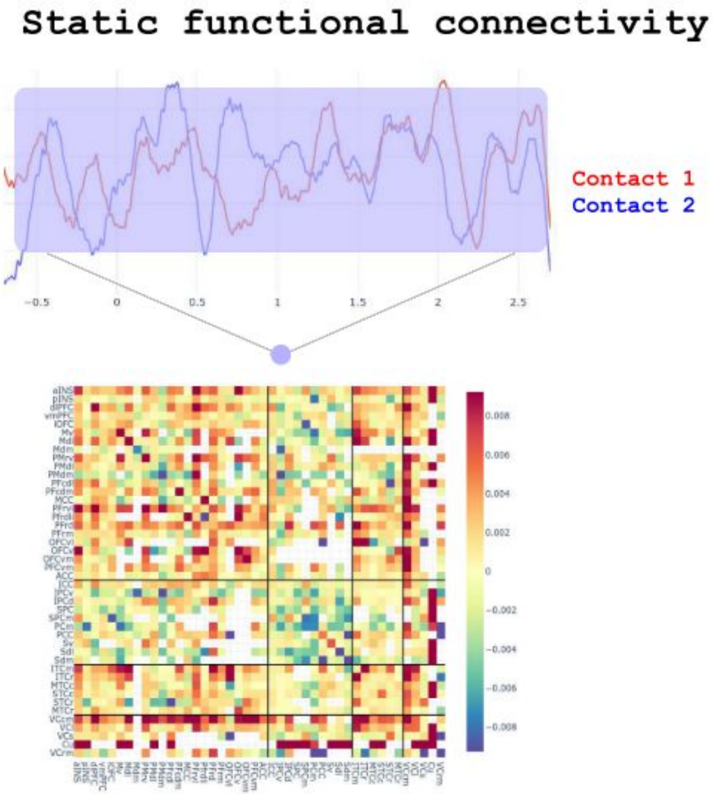
Bastos and Schoffelen (2016). A Tutorial Review of Functional Connectivity Analysis Methods and Their Interpretational Pitfalls. *Frontiers in Systems Neuroscience*

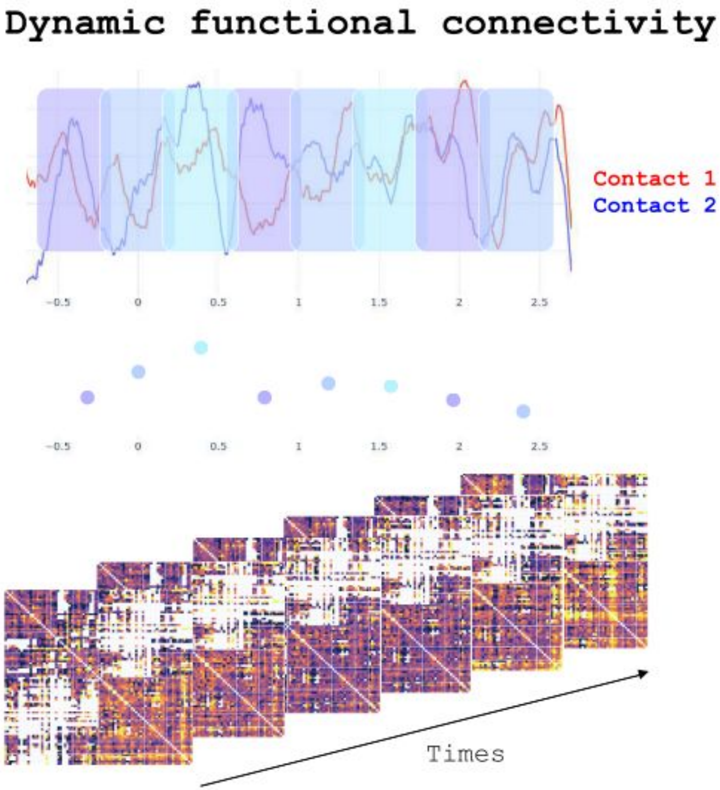
Functional Connectivity measures



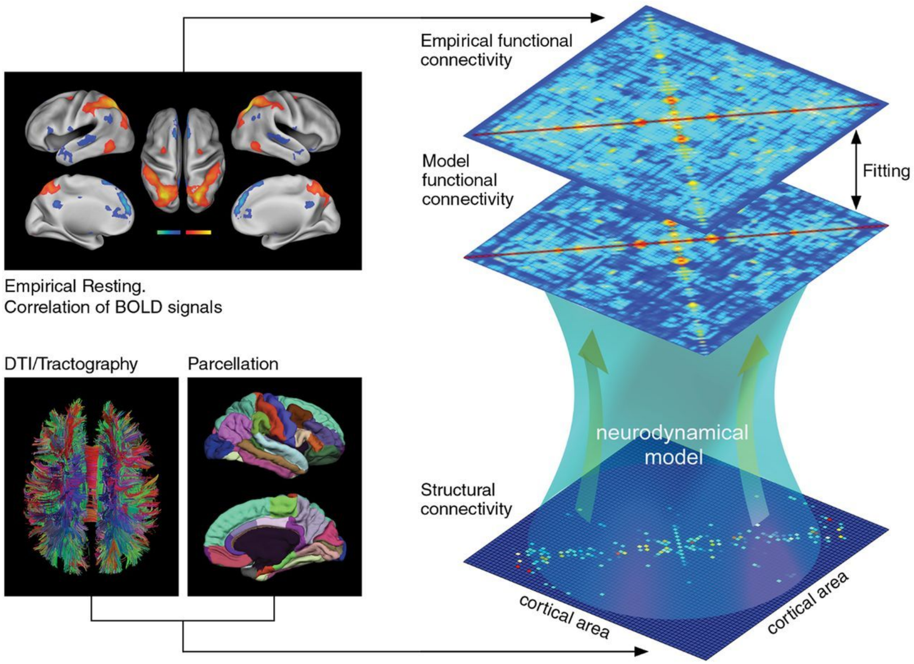
Bastos and Schoffelen (2016). A Tutorial Review of Functional Connectivity Analysis Methods and Their Interpretational Pitfalls. *Frontiers in Systems Neuroscience*

Functional Connectivity



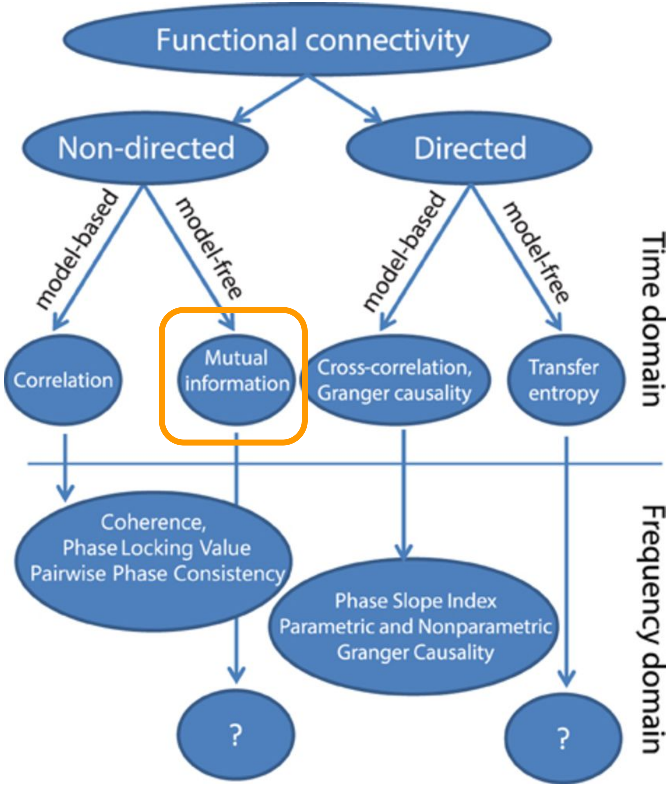


Brain models and neural interaction measures



Deco et al (2013) *JNeurosci*

Functional Connectivity measures



Bastos and Schoffelen (2016). A Tutorial Review of Functional Connectivity Analysis Methods and Their Interpretational Pitfalls. *Frontiers in Systems Neuroscience*

Information Theory

WIKIPEDIA
The Free Encyclopedia

Information theory (Shannon, 1948) is the scientific study of the quantification, storage, and communication of information

$$Surprisal = -\log P(X)$$

Level of "surprise" of a particular outcome
Information content

$$H(X) = -\sum_{i=1}^{N} P(X_i) \log P(X_i)$$

Average uncertainty in X
Expected value of information carried by X

$$I(X;Y) = H(X) - H(X|Y)$$

Amount of information carried by Y about X, and *vice versa*

$$I(X;Y|Z) = H(X;Z) - H(X|Z,Y)$$

Amount of information carried by Y about X (and *vice versa*) given the value of a third variable Z

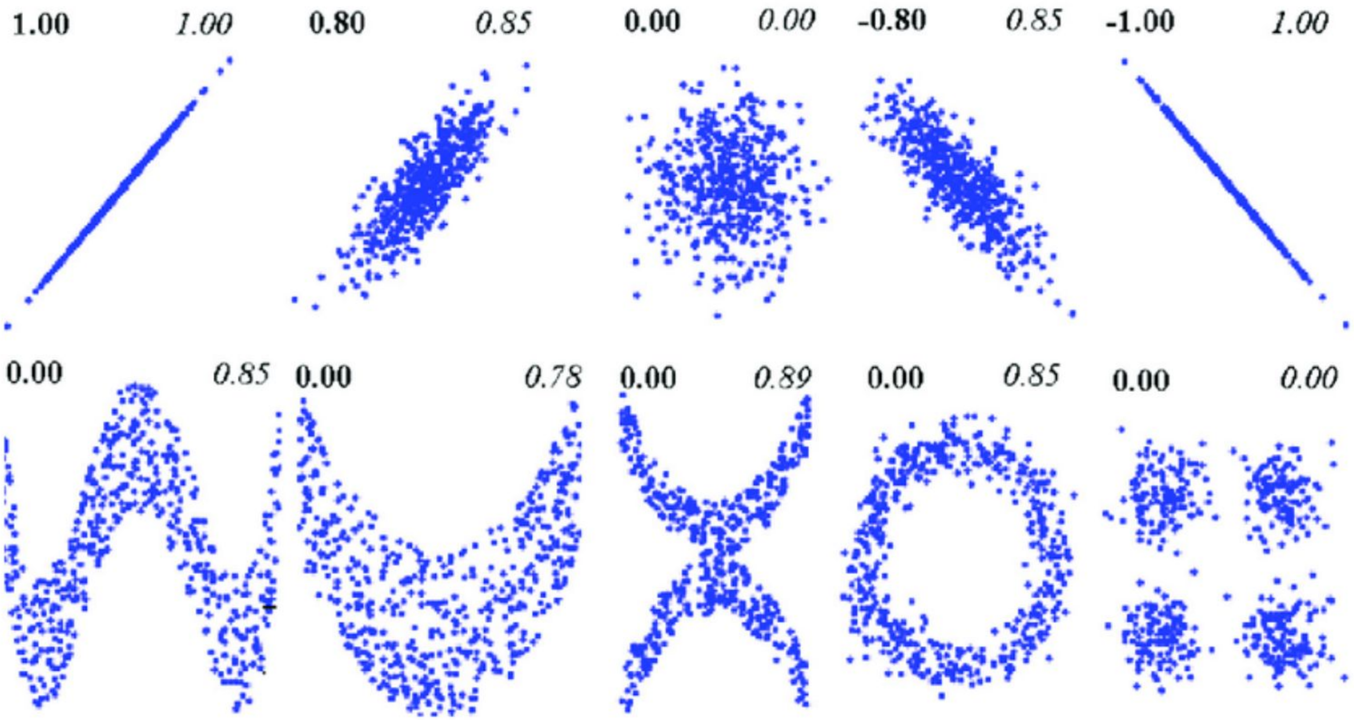
Mutual Information

$$H(X) = H(X|Y) \rightarrow \boldsymbol{Zero}\ Mutual\ Dependence$$
$$H(X) > H(X|Y) \rightarrow \boldsymbol{Positive}\ Mutual\ Dependece$$

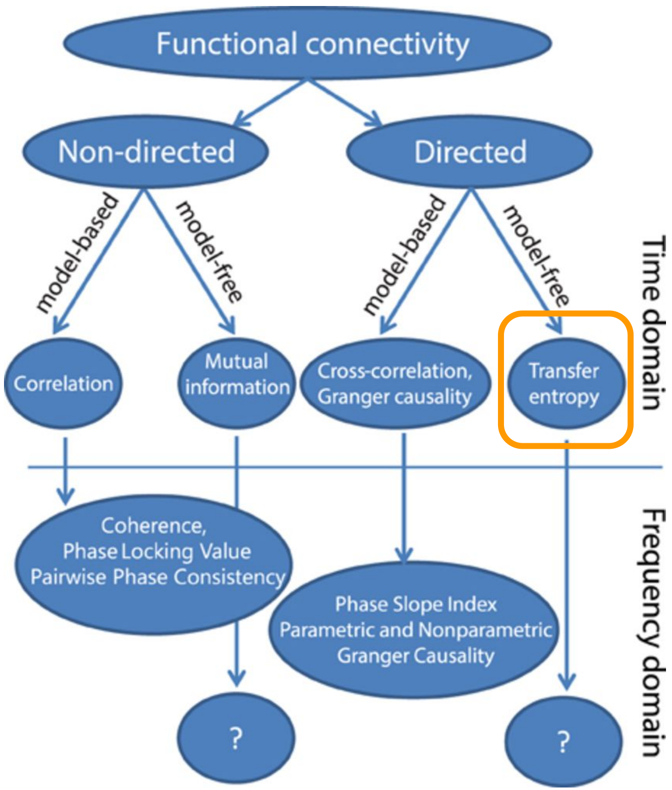
$$I(X;Y) = H(X) - H(X|Y)$$

Amount of mutual information between X and Y

Mutual Information vs Linear Correlation

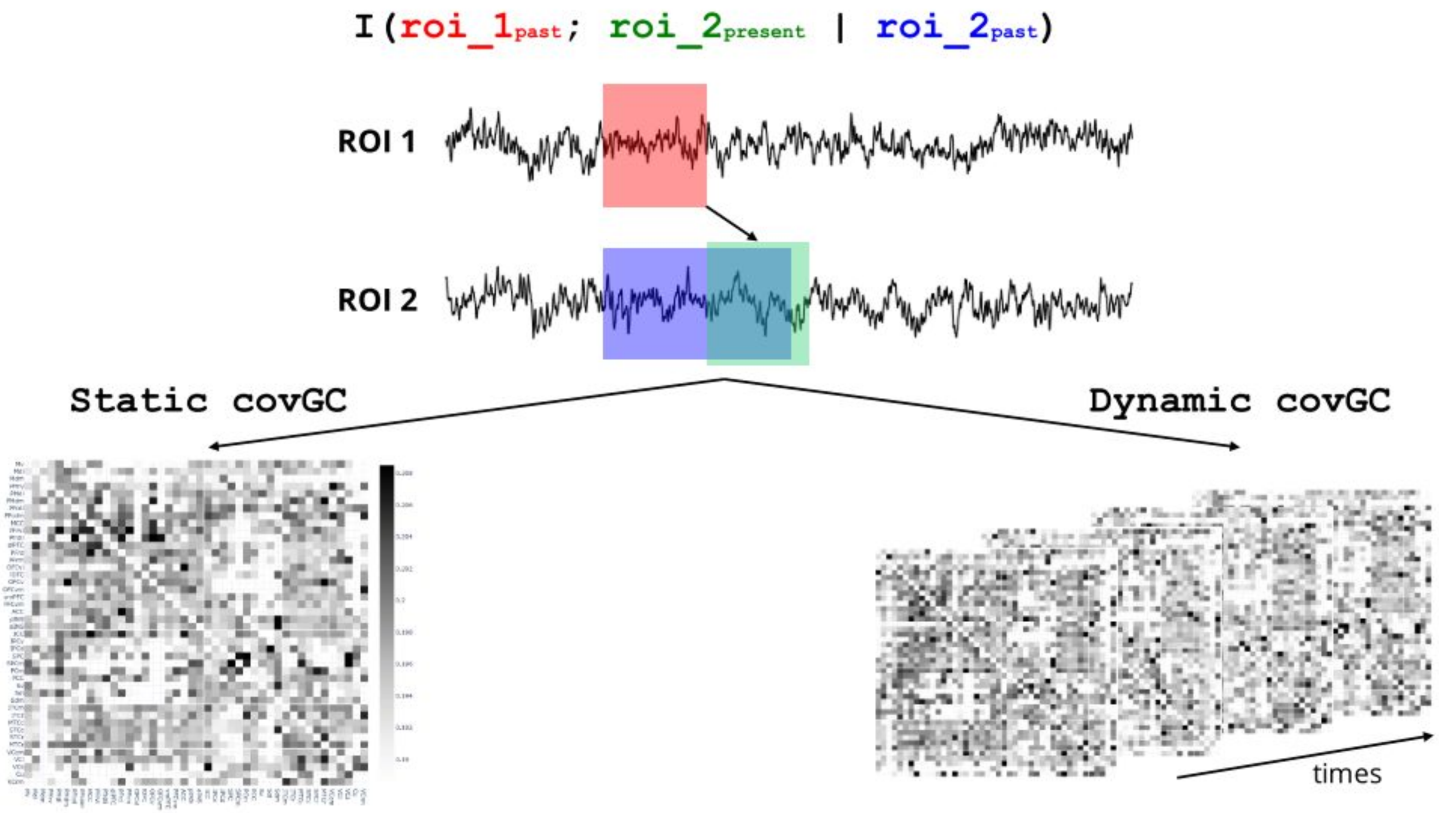


Functional Connectivity measures

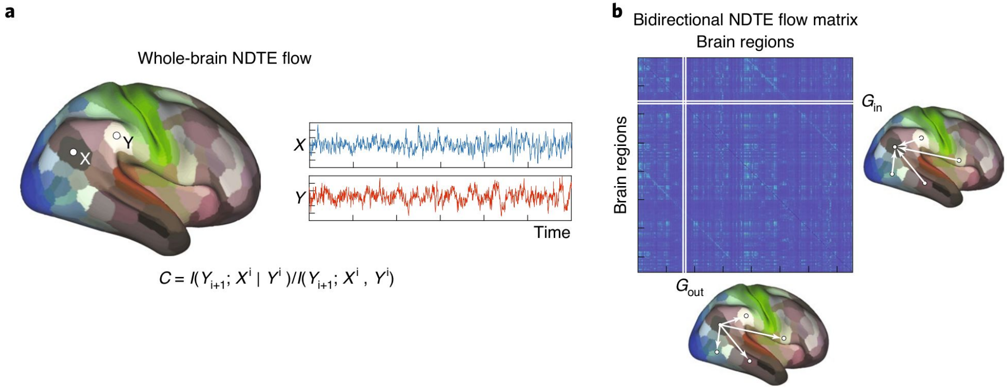


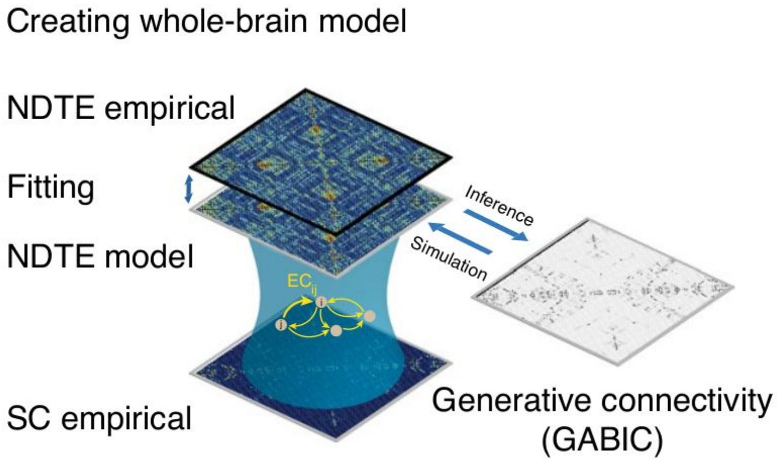
Bastos and Schoffelen (2016). A Tutorial Review of Functional Connectivity Analysis Methods and Their Interpretational Pitfalls. *Frontiers in Systems Neuroscience*

Transfer Entropy



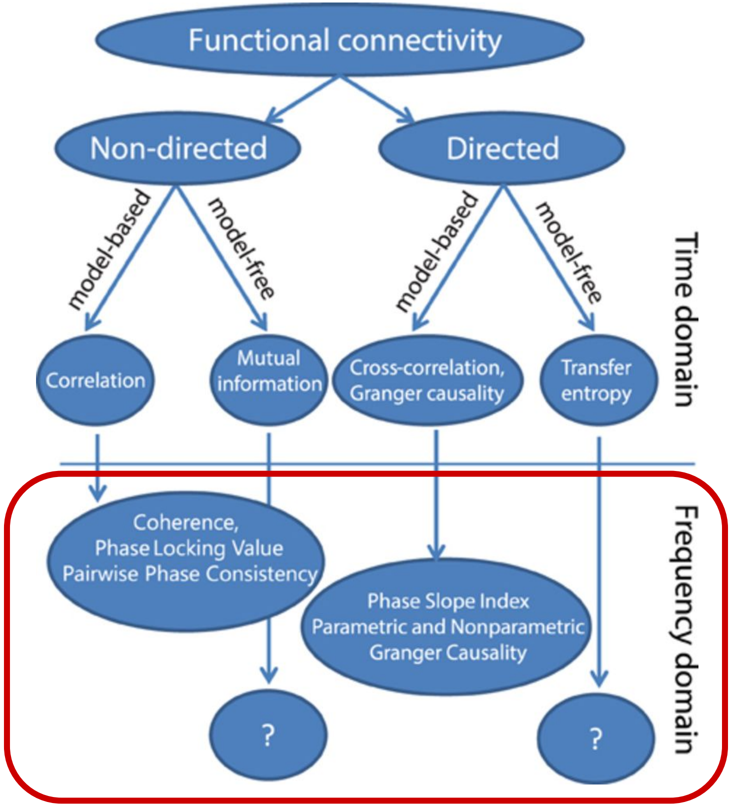
Brain models and neural interaction measures





Deco et al (2021) *Nature Human Behaviour*

Functional Connectivity measures



Bastos and Schoffelen (2016). A Tutorial Review of Functional Connectivity Analysis Methods and Their Interpretational Pitfalls. *Frontiers in Systems Neuroscience*

1. Information Decomposition

2. Higher-order interactions

3. Feature-specific Information Transfer

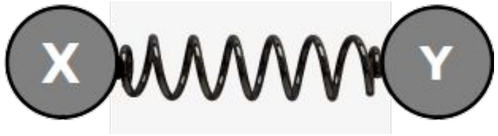
1. Information Decomposition

2. Higher-order interactions

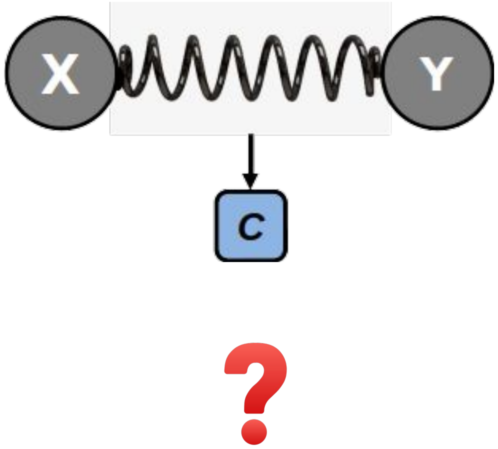
3. Feature-specific Information Transfer

Task-related neural interactions

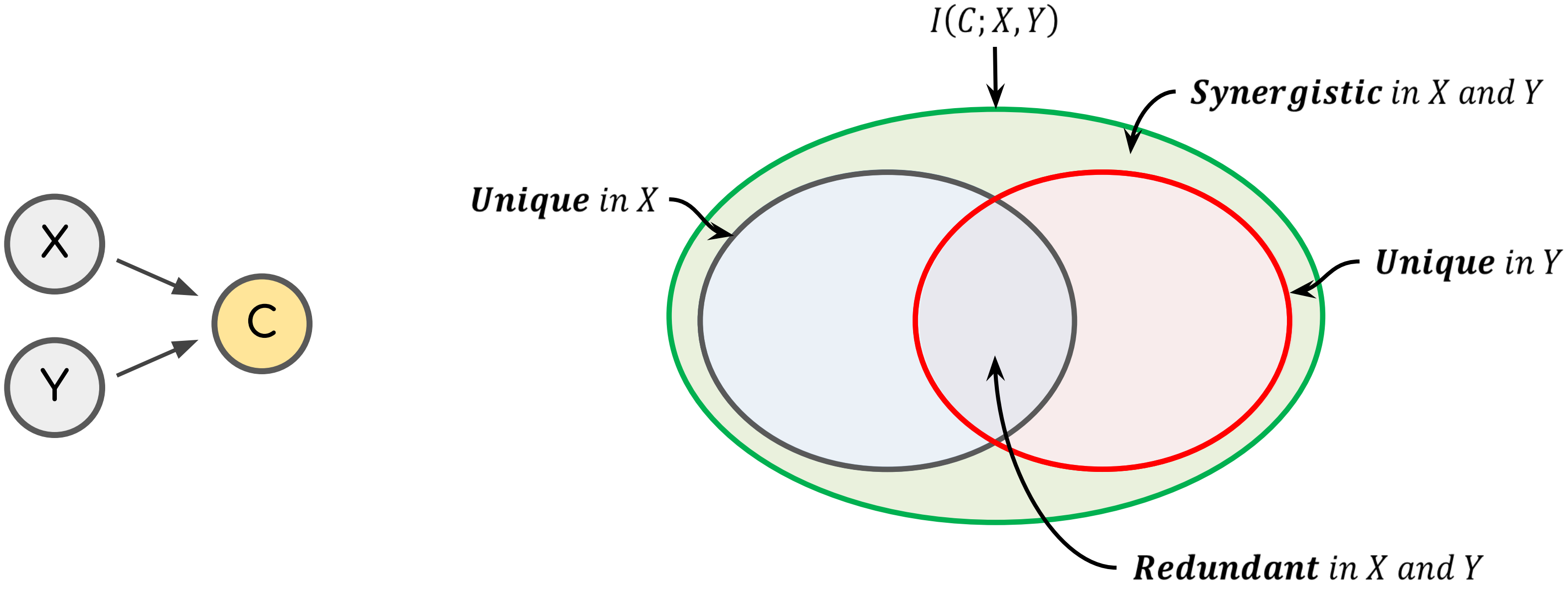
Amount of inter-areal dependence
(FC and FCD)



Amount and “Content”
of inter-areal dependence

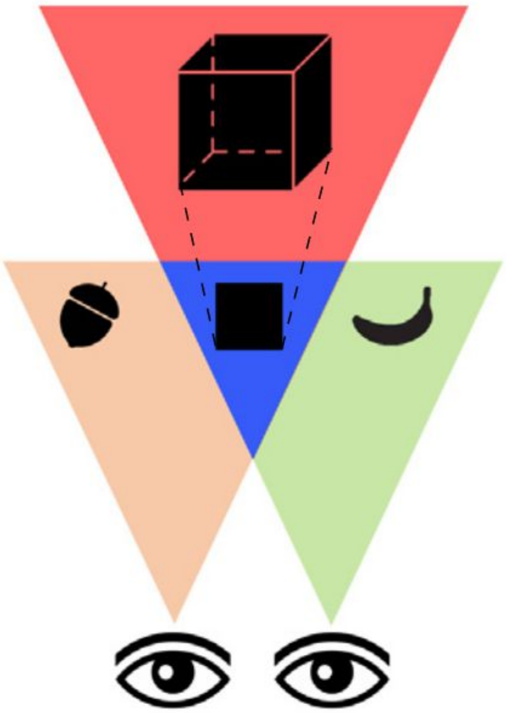


Partial Information Decomposition



Williams and Beer (2010); Wibral et al. (2017); Lizier et al. (2018)

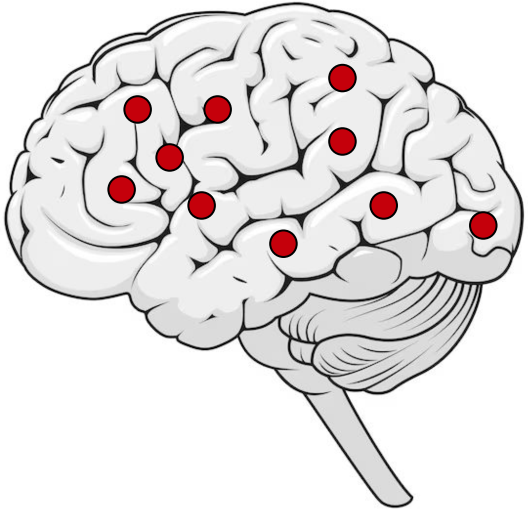
Information Decomposition

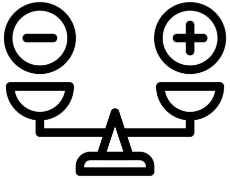


Luppi et al. (2024) *TINS*

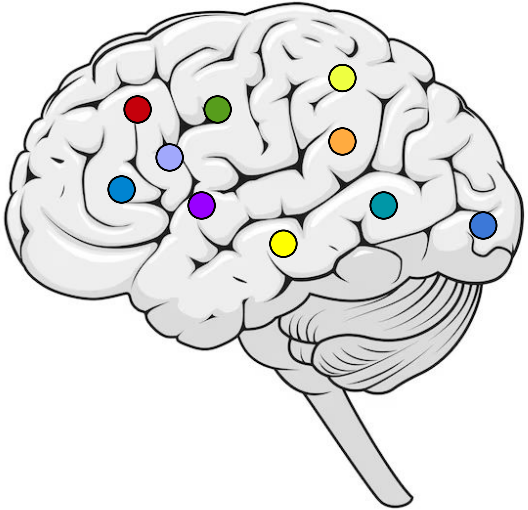
Distributed encoding through brain interactions

Redundant ***encoding***





Synergistic ***encoding***



Pros: robust/resilient
Cons: inefficient

Pros: efficient
Cons: fragile

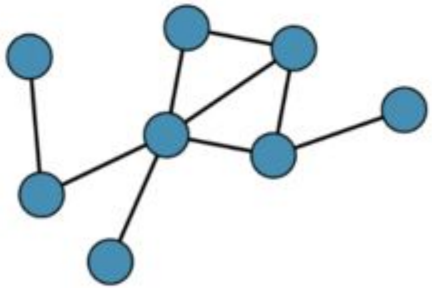
1. Information Decomposition

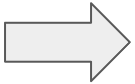
2. Higher-order interactions

3. Feature-specific Information Transfer

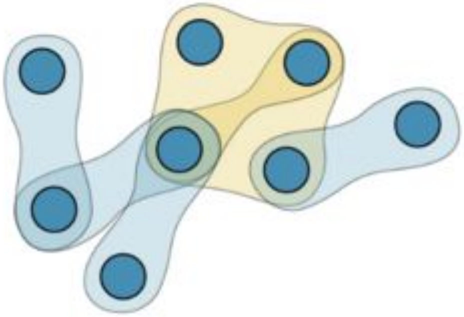
Graphs represents pairwise interactions

Pairwise interactions





Higher-order interactions



Network Science

nature physics

PERSPECTIVE

https://doi.org/10.1038/s41567-021-01371-4

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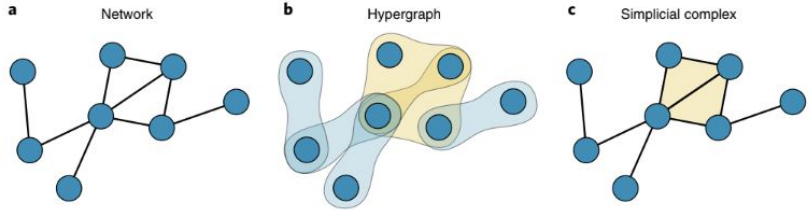
The physics of higher-order interactions in complex systems

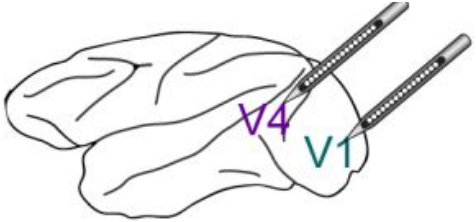
Federico Battiston[1]✉, Enrico Amico[2,3], Alain Barrat[4,5], Ginestra Bianconi[6,7], Guilherme Ferraz de Arruda[8], Benedetta Franceschiello[9,10], Iacopo Iacopini[1], Sonia Kéfi[11,12], Vito Latora[6,13,14,15], Yamir Moreno[8,15,16,17], Micah M. Murray[9,10,18], Tiago P. Peixoto[1,19], Francesco Vaccarino[20] and Giovanni Petri[8,21]✉

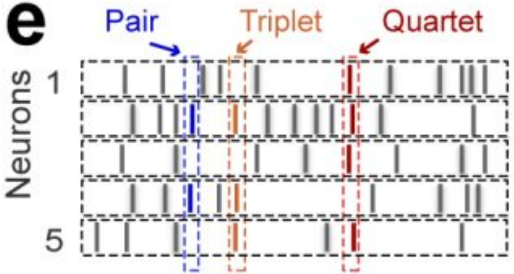
Complex networks have become the main paradigm for modelling the dynamics of interacting systems. However, networks are intrinsically limited to describing pairwise interactions, whereas real-world systems are often characterized by higher-order interactions involving groups of three or more units. Higher-order structures, such as hypergraphs and simplicial complexes, are therefore a better tool to map the real organization of many social, biological and man-made systems. Here, we highlight recent evidence of collective behaviours induced by higher-order interactions, and we outline three key challenges for the physics of higher-order systems.

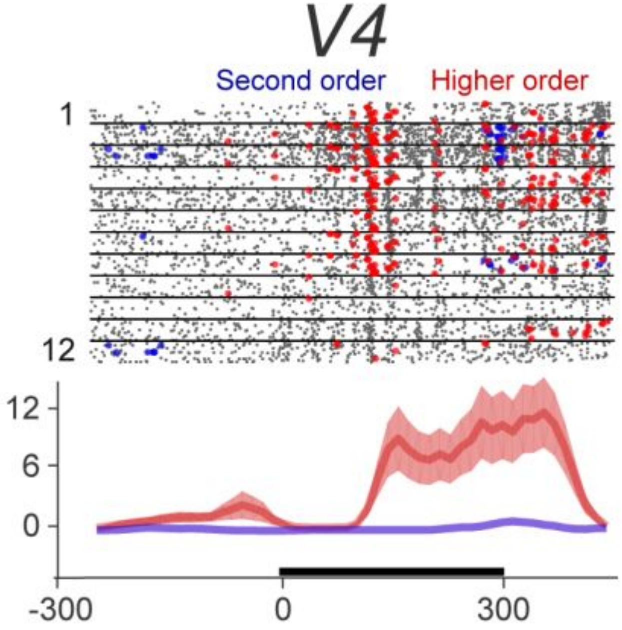
How to represent HOIs



High-order collective behaviors in the brain

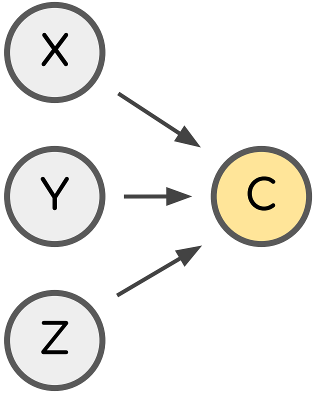


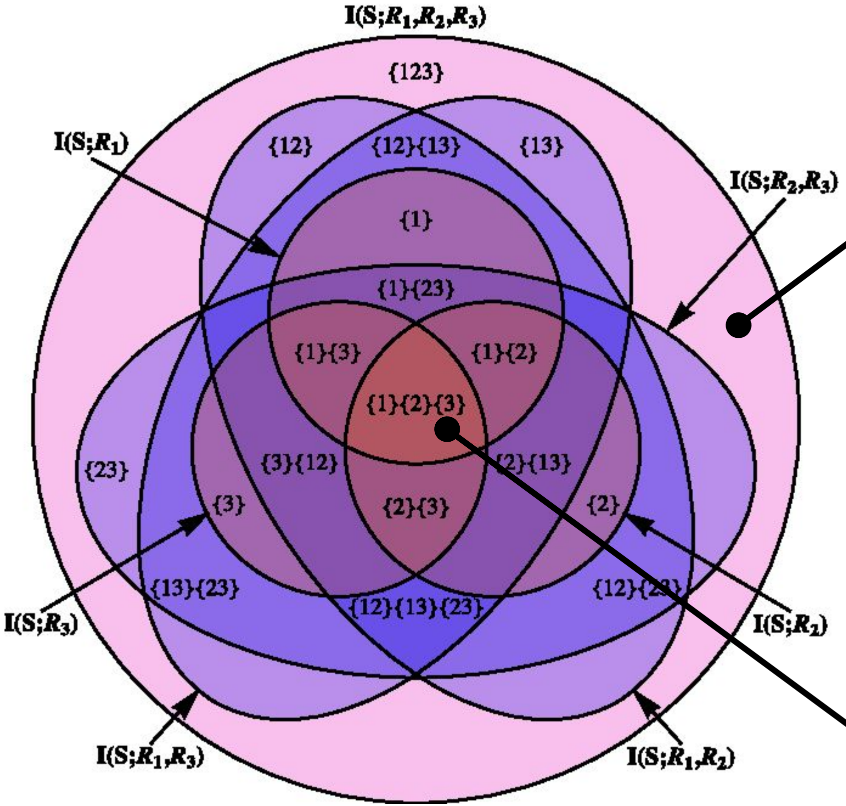




Shahidi et al. (2019) *Nature Neurosci*

Higher-Order Information Decomposition





Higher-order

<u>synergistic</u> *information*

Higher-order

<u>redundant</u> *information*

Dedekind number

M(2) = 4

M(3) = 18

M(4) = 166

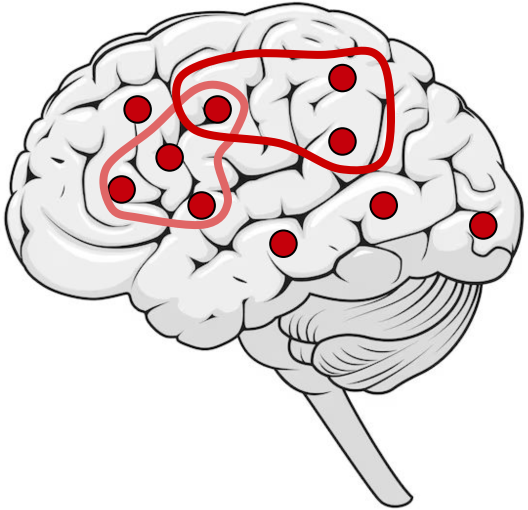
M(5) = 7580

M(6) = 7828354

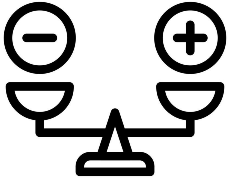
M(7) = 2414682040998

Encoding through higher-order brain interactions

***Redundant* encoding**

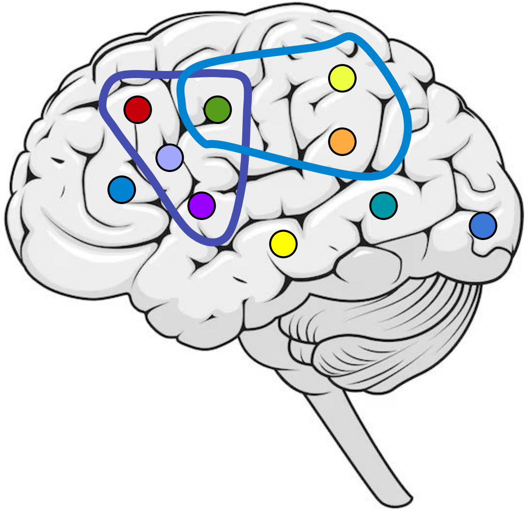


Pros: robust/resilient
Cons: inefficient



Hebb, Hopfield, Singer, Abeles, Bialek, Buzsaki, Aertsen, Varela, Bressler, Deco, Breakspear, etc

***Synergistic* encoding**



Pros: efficient
Cons: fragile

Information Theory for collective behavior

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covering statistical, nonlinear, biological, and soft matter physics

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Quantifying high-order interdependencies via multivariate extensions of the mutual information

Fernando E. Rosas, Pedro A. M. Mediano, Michael Gastpar, and Henrik J. Jensen
Phys. Rev. E **100**, 032305 – Published 13 September 2019

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frontiers in Physiology

METHODS
published: 14 January 2021
doi: 10.3389/fphys.2020.595736

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Quantifying Dynamical High-Order Interdependencies From the O-Information: An Application to Neural Spiking Dynamics

Sebastiano Stramaglia[1,2], Tomas Scagliarini[1], Bryan C. Daniels[3] and Daniele Marinazzo[4]*

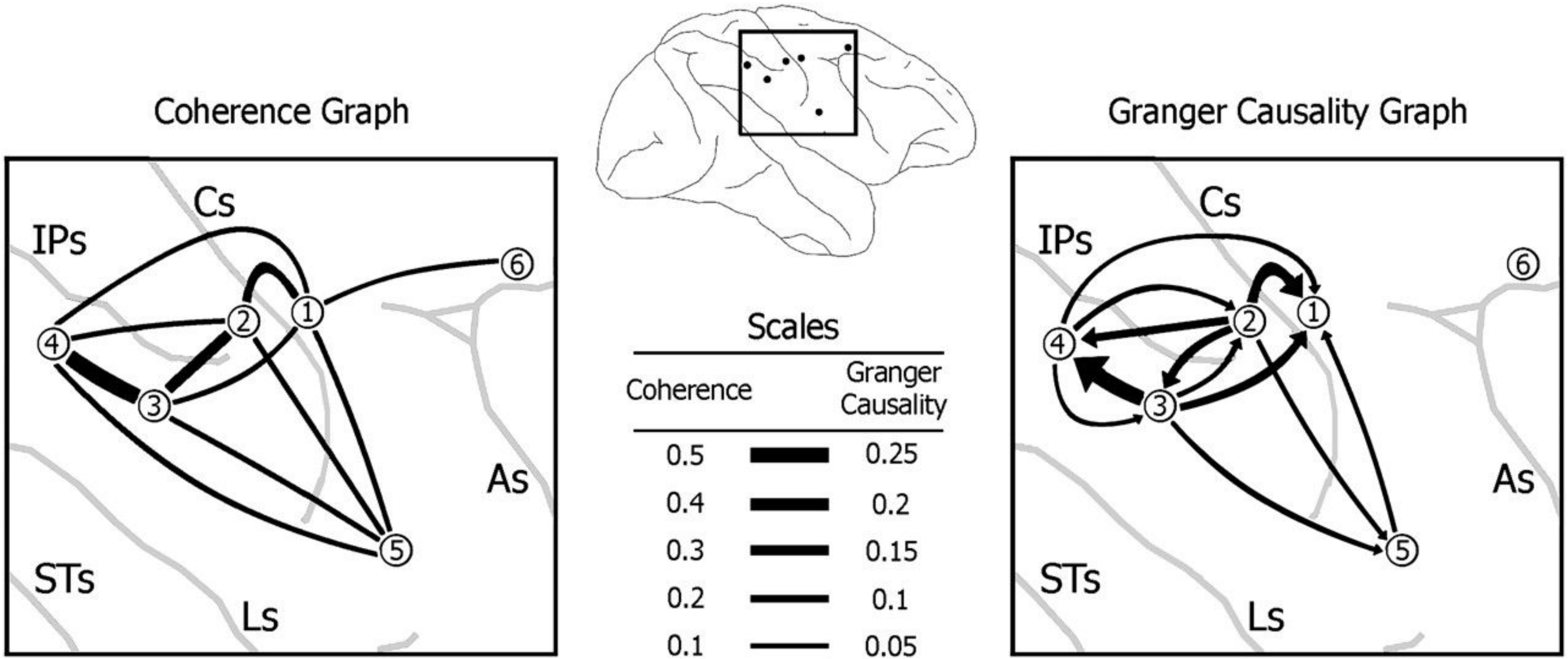
[1] Dipartimento Interateneo di Fisica, Universitá degli Studi Aldo Moro, Bari and INFN, Bari, Italy, [2] Center of Innovative Technologies for Signal Detection and Processing (TIRES), Universitá degli Studi Aldo Moro, Bari, Italy, [3] Arizona State University and Santa Fe Institute Center for Biosocial Complex Systems, Arizona State University, Tempe, AZ, United States, [4] Department of Data Analysis, Ghent University, Ghent, Belgium

1. Information Decomposition

2. Higher-order interactions

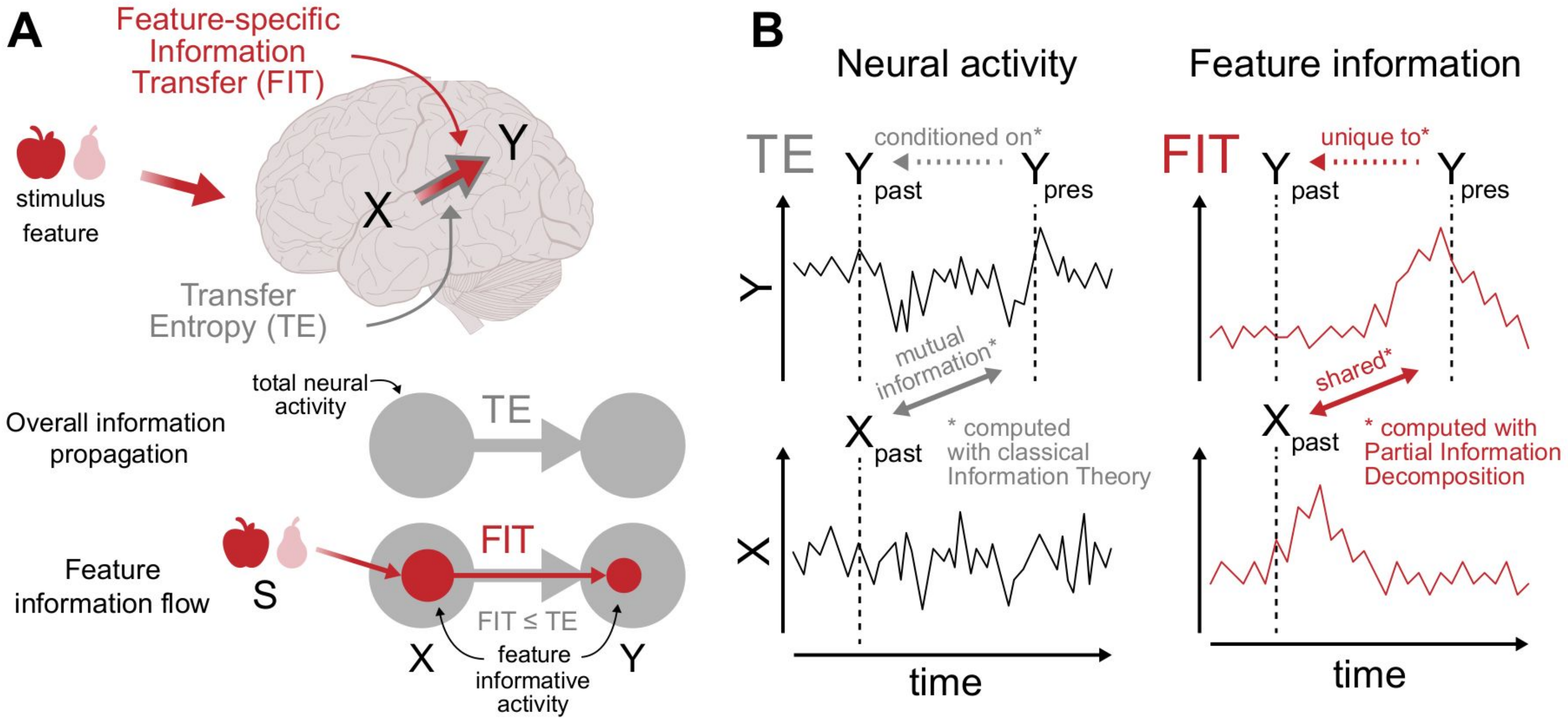
3. Feature-specific Information Transfer

Broadcasting of information



Brovelli A et al (2004) *PNAS*

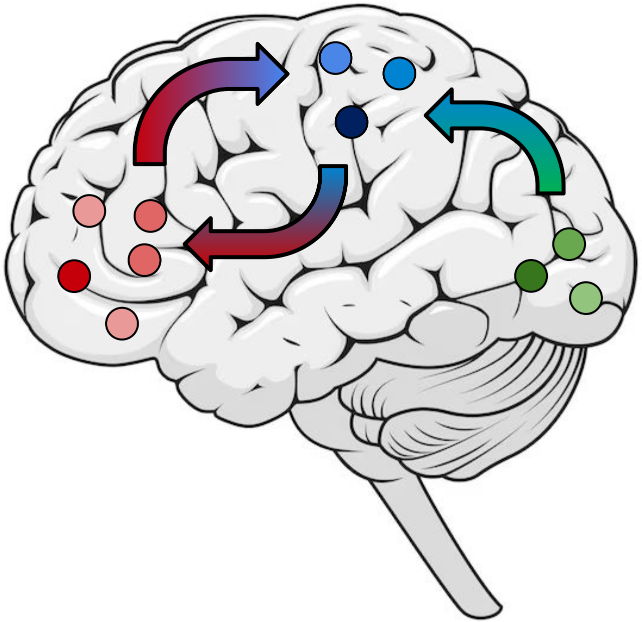
Broadcasting of information relevant for cognition



Celotto M, …, Brovelli A, Panzeri S (2023) *NeurIPS*

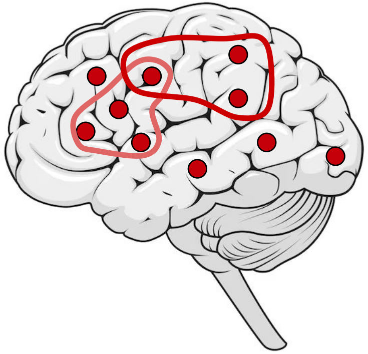
Broadcasting of information relevant for cognition

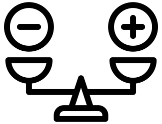
Task-specific information flow



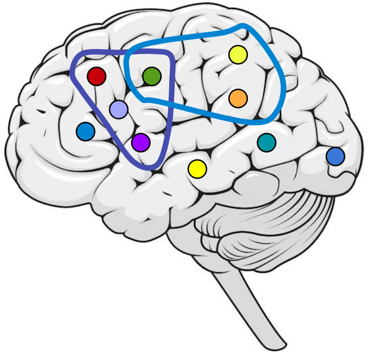
Distributed higher-order encoding and broadcast of information relevant for cognitive functions

***Redundant* encoding**

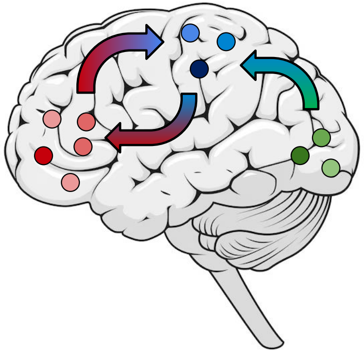




***Synergistic* encoding**



Information Flow



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Pros: efficient
Cons: fragile

Fries, Bressler, Vinck, Panzeri

1. **Neural interactions in the human frontal cortex dissociate reward and punishment learning**
   Combrisson E, Basanisi R, Gueguen MCM, Rheims S, Kahane P, Bastin P, Brovelli A
   eLife (2024)

2. **Higher-order and synergistic functional interactions encode <u>information gain</u> in goal-directed learning**
   Combrisson E*, Basanisi R*, Neri M, Auzias G, Petri G, Marinazzo D, Panzeri S, Brovelli A
   Nat Commun (2025)

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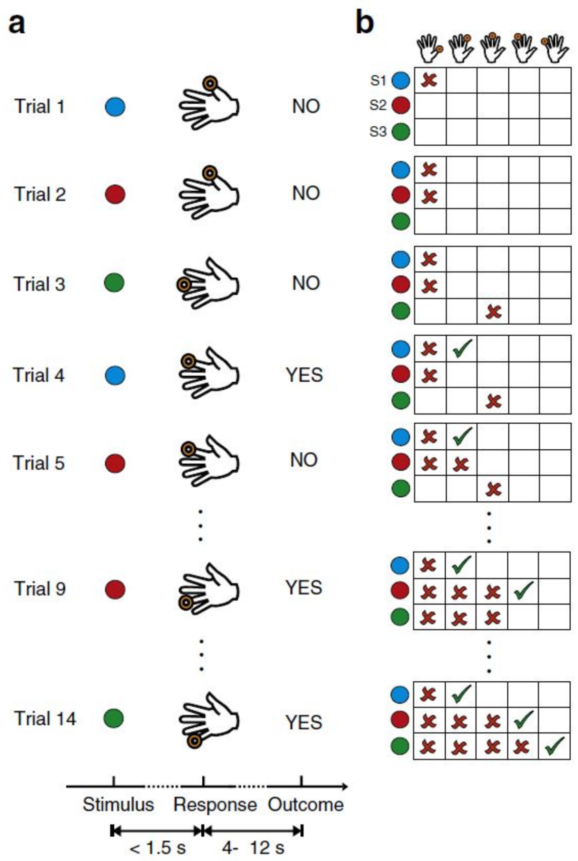
   Nat Commun (2025)

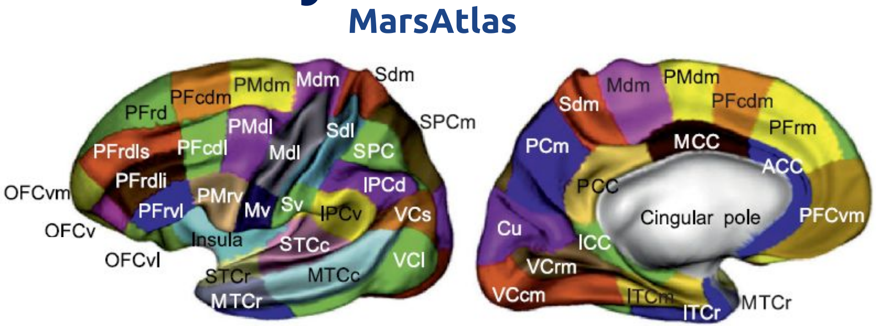
Goal-directed information seeking task

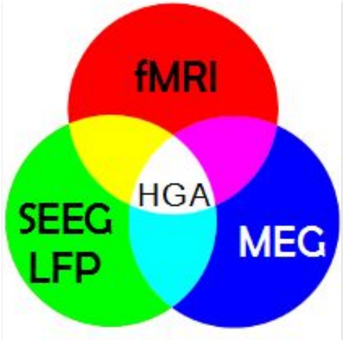


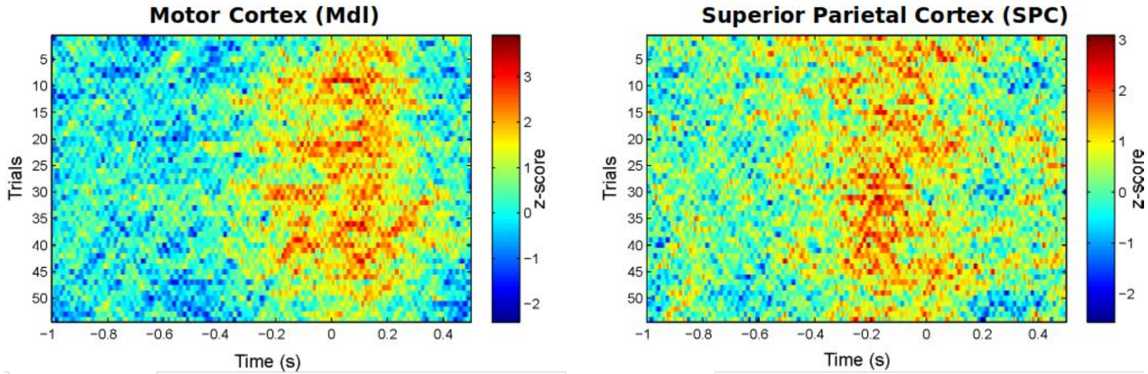
*Deterministic **causal** relations between stimuli, actions and outcomes*

Broadband High-Gamma Activity

MEG, cortical-level, single-trial



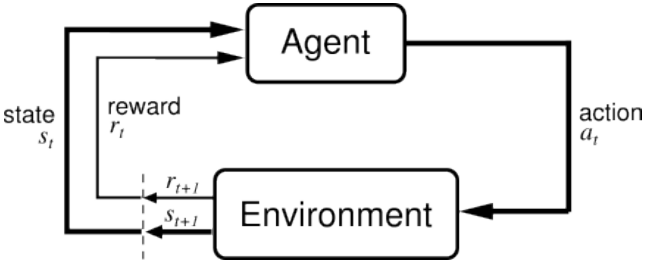




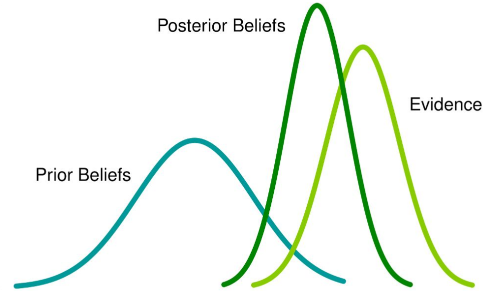
Brovelli et al (2015) JNeurosci
Auzias, Coulon and Brovelli (2016) *Human Brain Mapping*
Brovelli et al (2017) JNeurosci

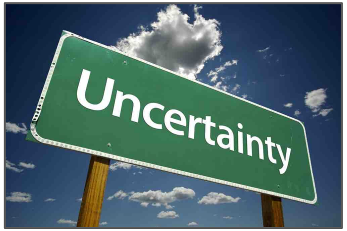
Learning theories

Reinforcement Learning



Bayesian Inference

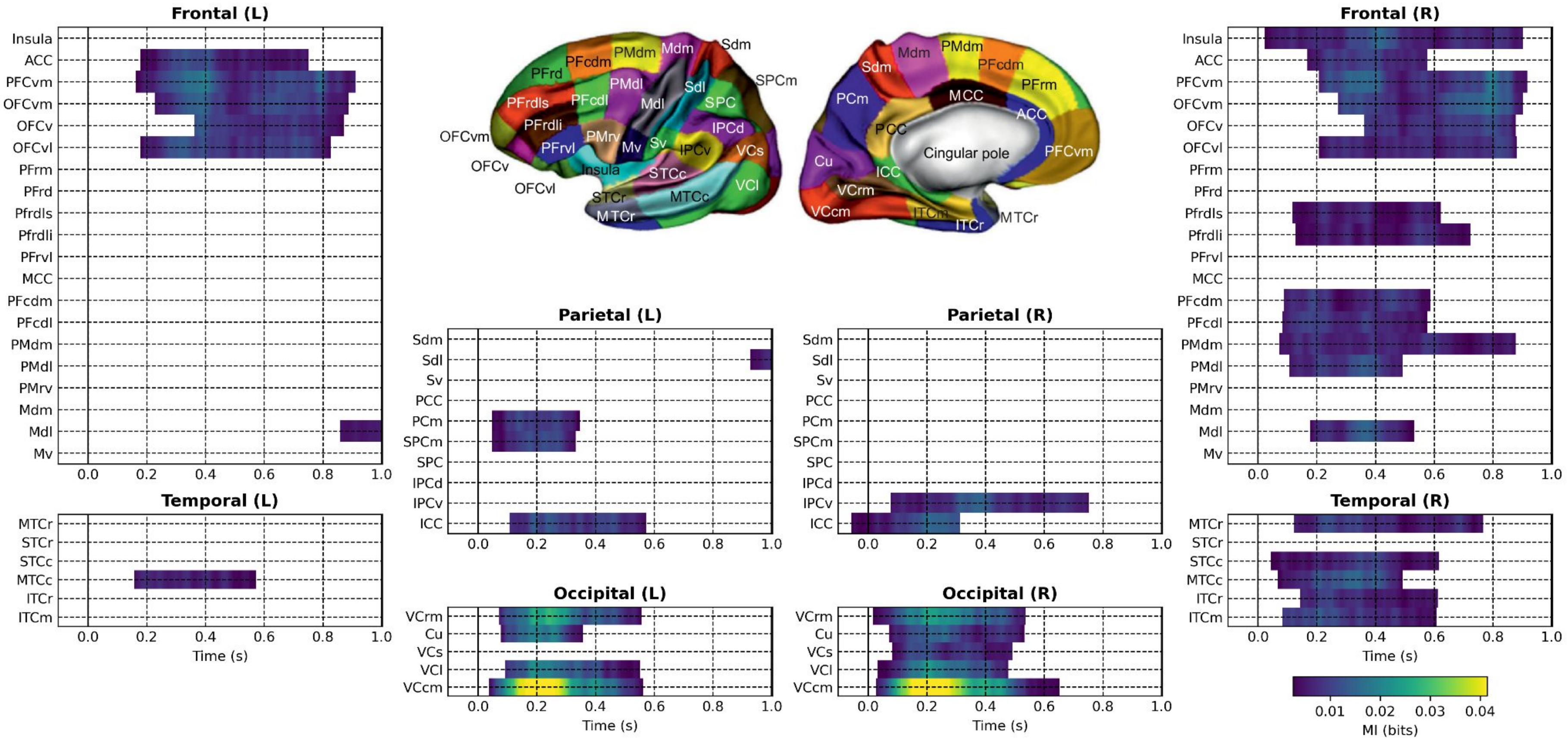




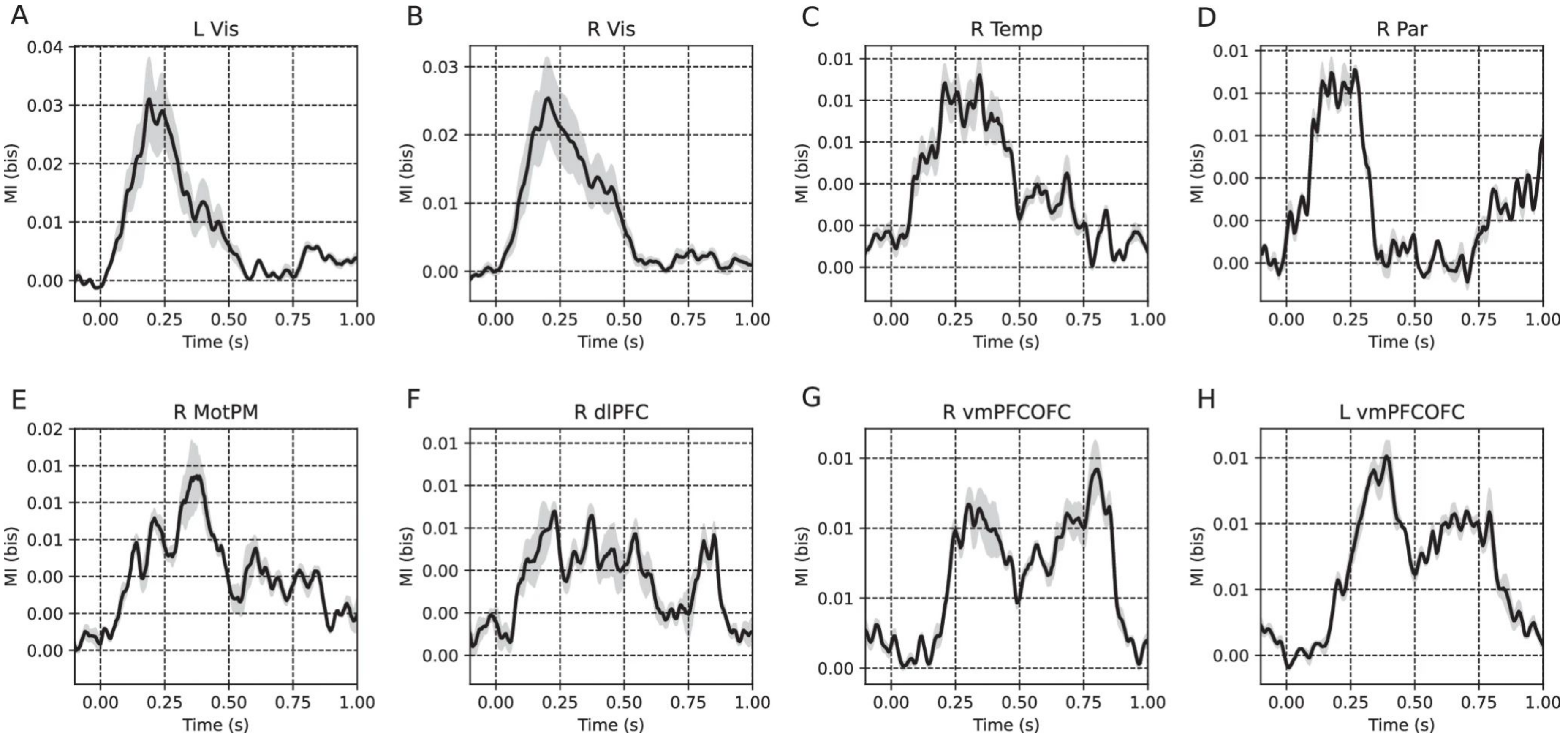
Reward Prediction Errors

Information Gain

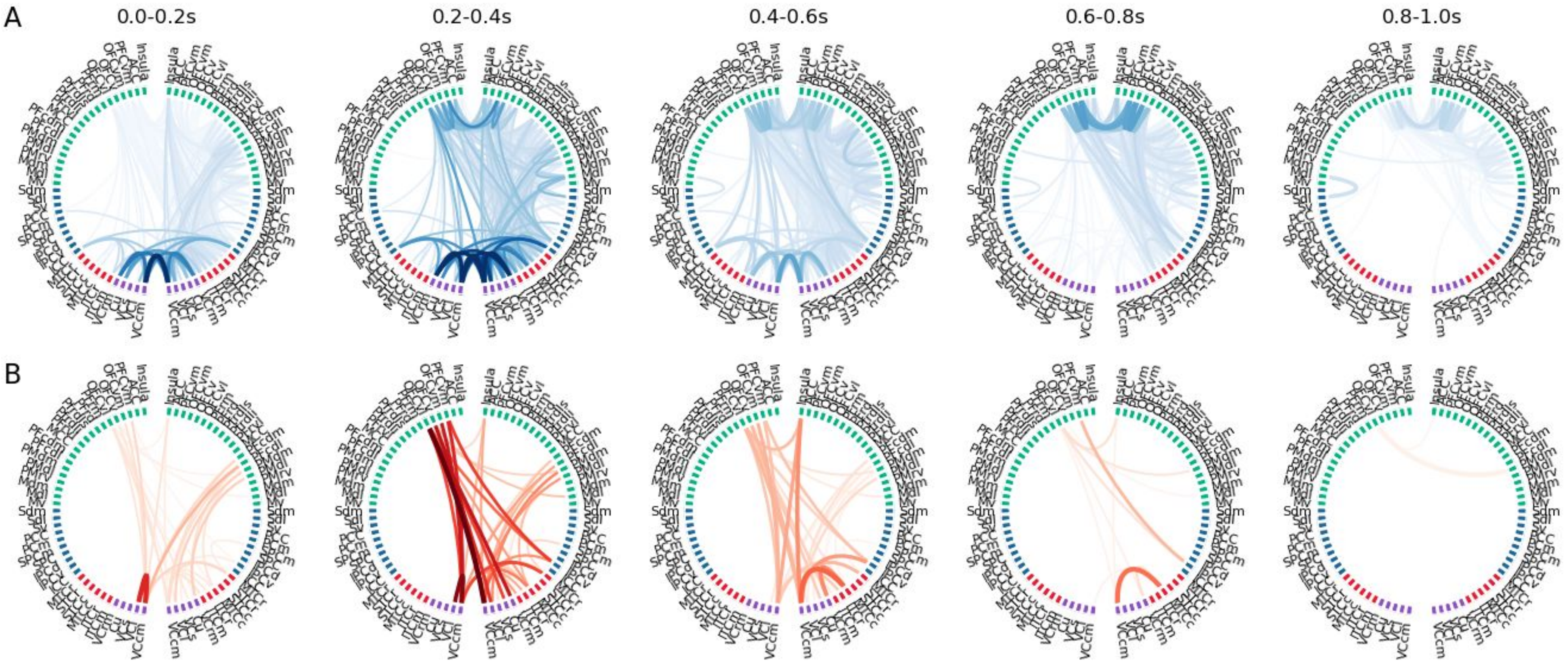
Local encoding of Information Gain



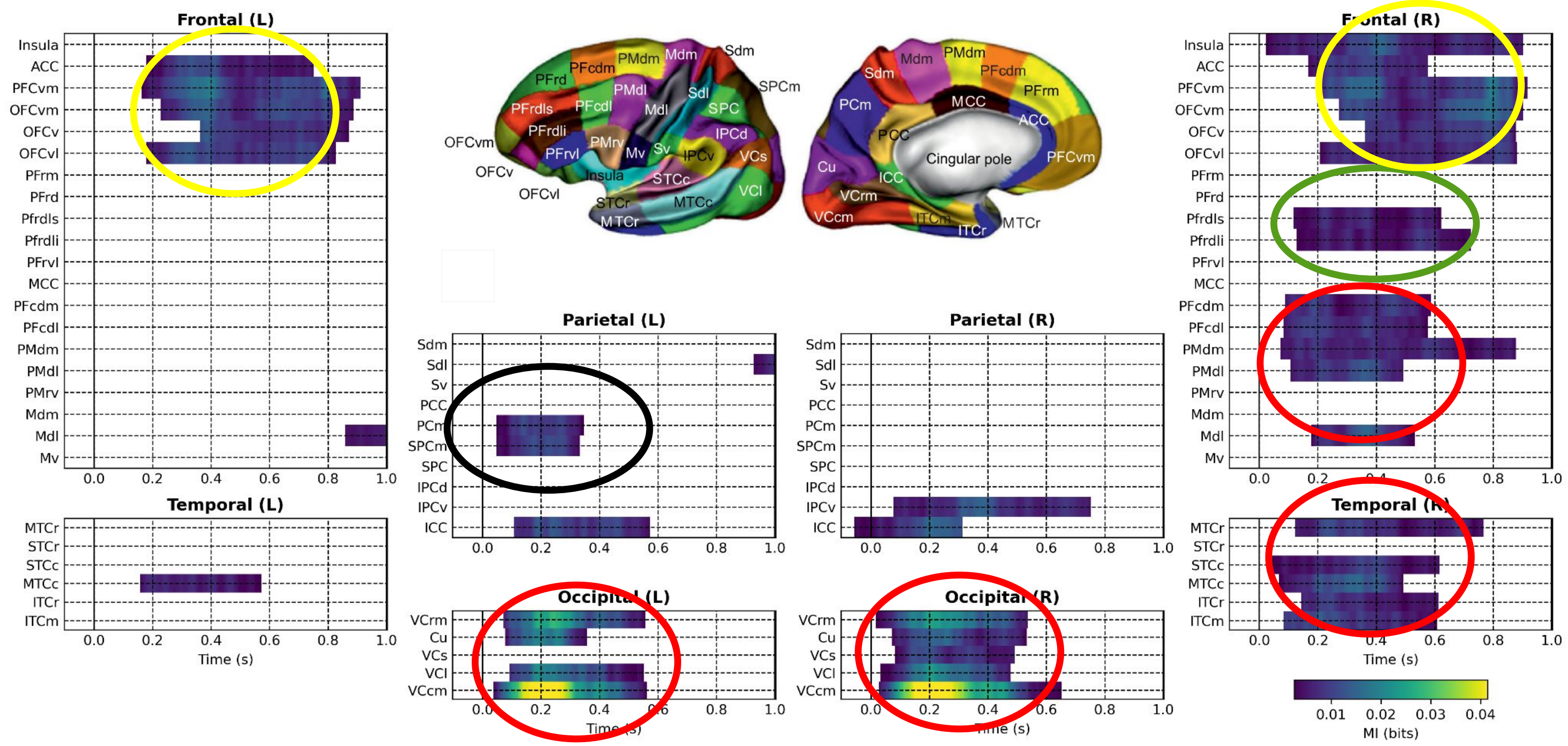
Local encoding of Information Gain



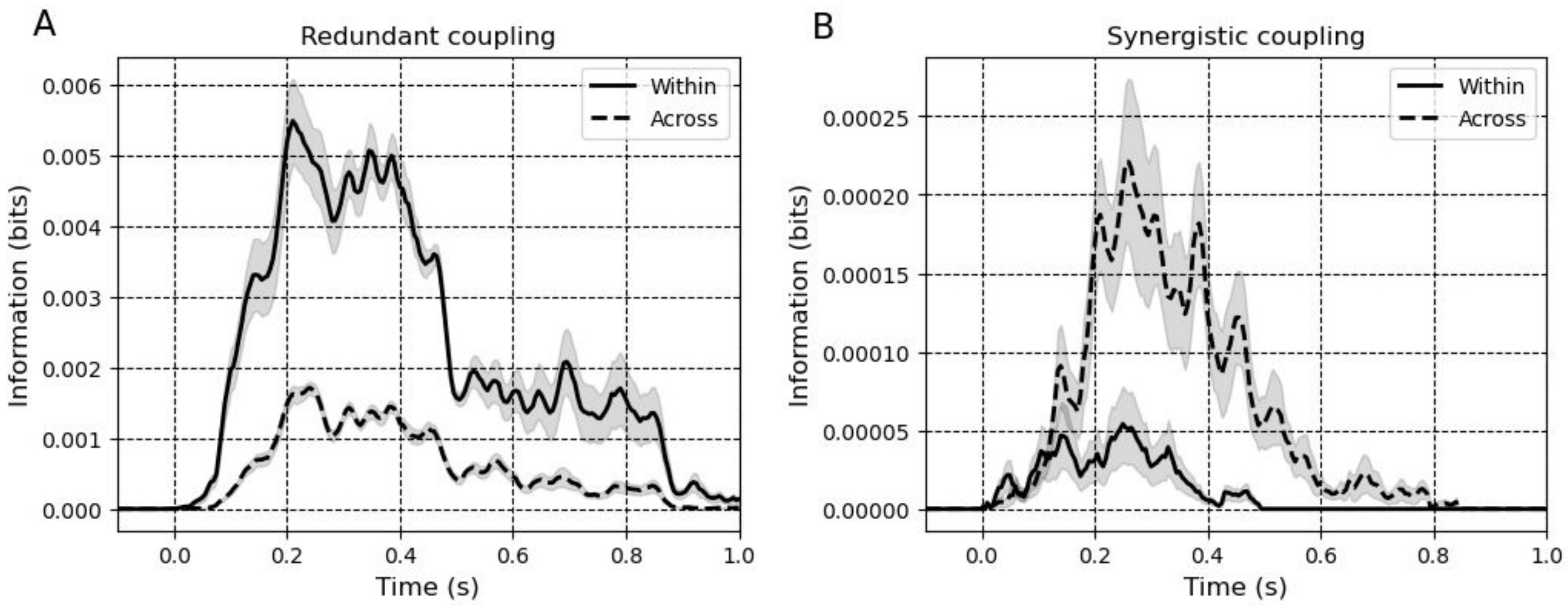
Distributed encoding of IG by redundant and synergistic interactions



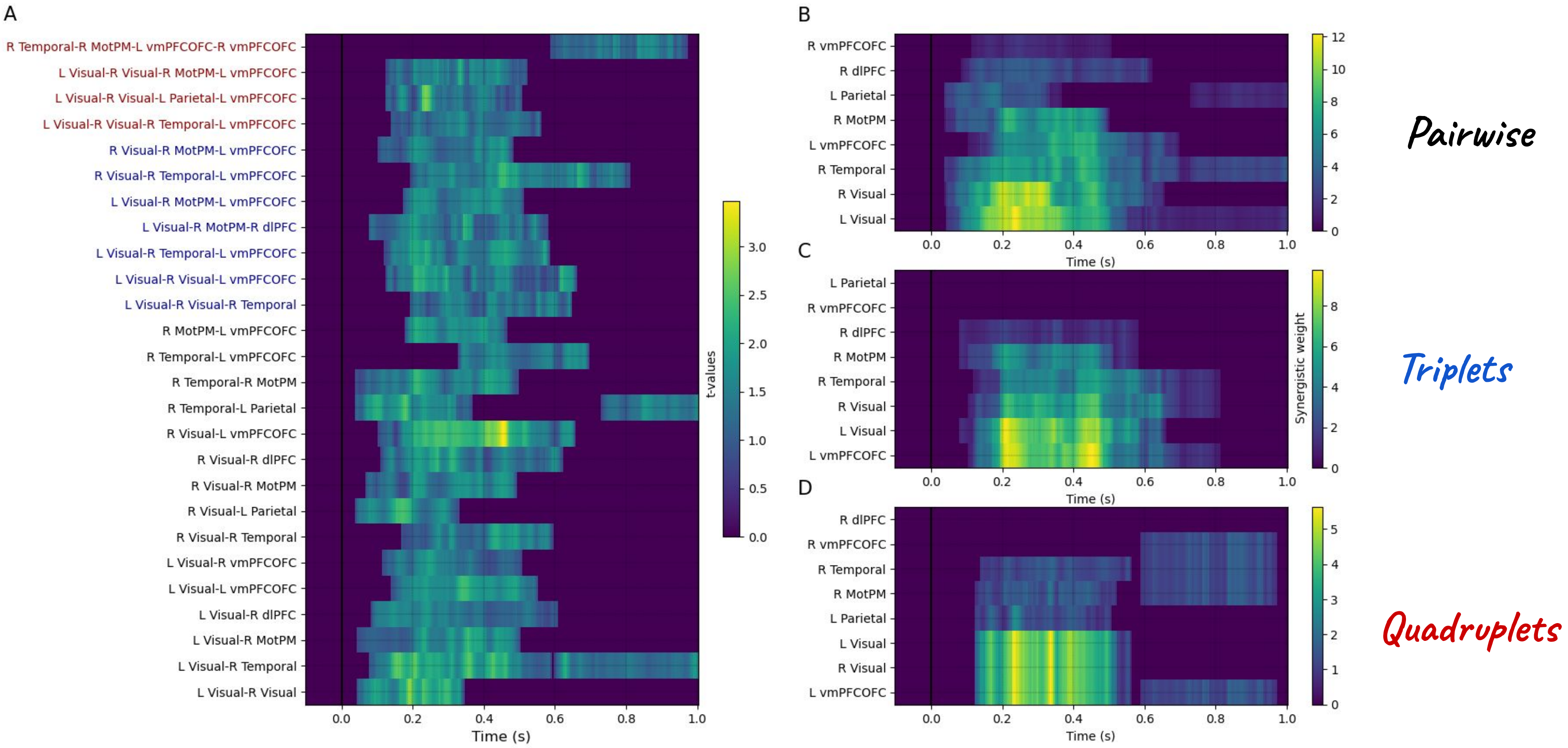
Integration *versus* Segregation?



Integration *versus* Segregation?

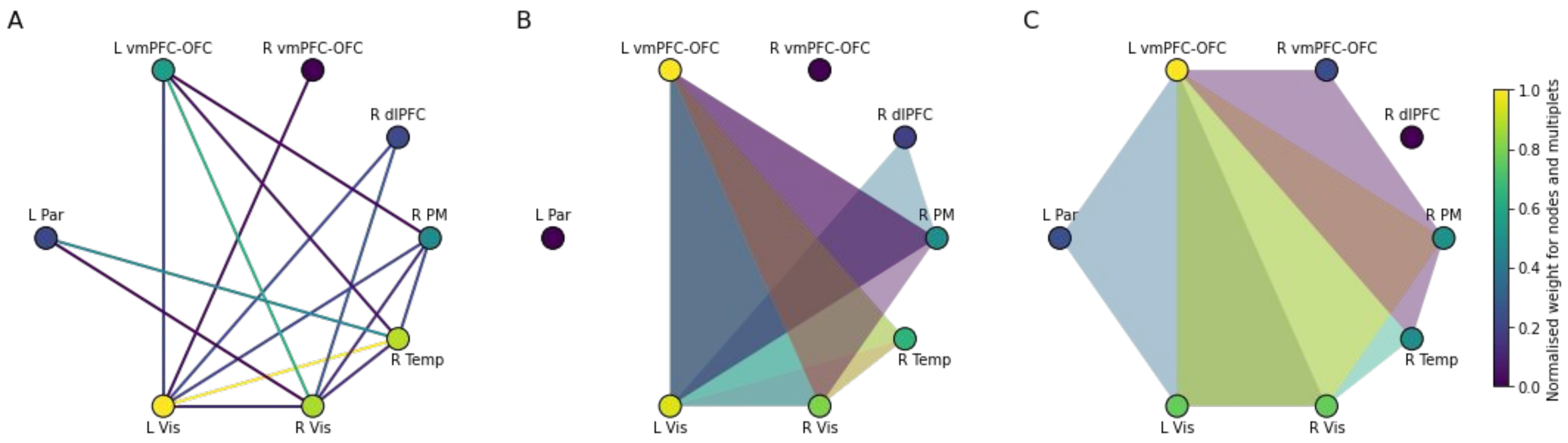


Higher-order and synergistic encoding

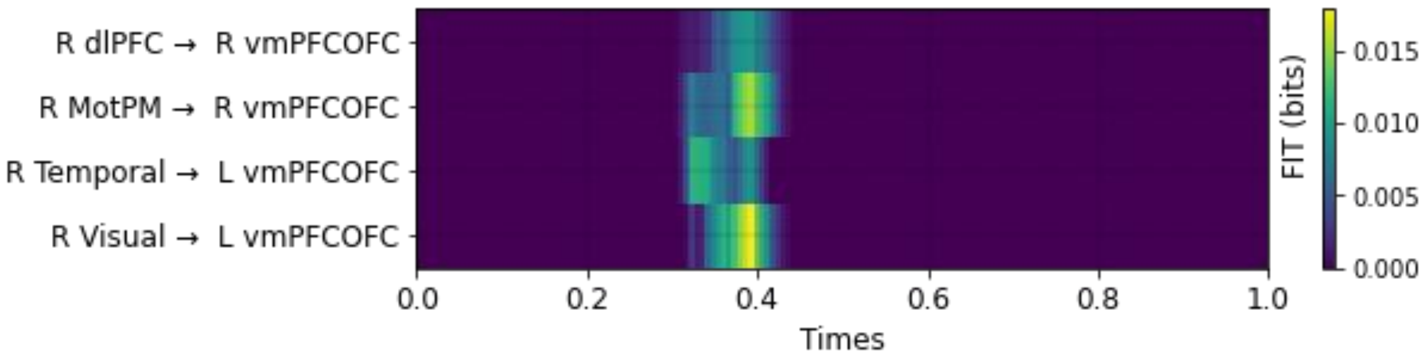


Higher-order overlap and synergistic encoding

Pairwise *Triplets* *Quadruplets*



Broadcasting of information along HOI synergistic interactions



Try it at home!

FRamework for
Information
Theoretical analysis of
Electrophysiological data and
Statistics

Higher
Order
Interactions

https://github.com/brainets/frites

https://brainets.github.io/frites/

Combrisson et al (2022) *JOSS*

https://github.com/brainets/hoi

https://brainets.github.io/hoi/

Neri et al (2024) *JOSS*

EBRAINS

NeuroImage 258 (2022) 119347

Contents lists available at ScienceDirect

NeuroImage

journal homepage: www.elsevier.com/locate/neuroimage

Group-level inference of information-based measures for the analyses of cognitive brain networks from neurophysiological data

Etienne Combrisson [a,*], Michele Allegra [a,d,e], Ruggero Basanisi [a], Robin A.A. Ince [b], Bruno L. Giordano [a], Julien Bastin [c], Andrea Brovelli [a,*]

[a] Aix Marseille Univ, CNRS, INT, Institut de Neurosciences de la Timone, Marseille, France
[b] School of Psychology and Neuroscience, University of Glasgow, Glasgow, UK
[c] Univ. Grenoble Alpes, Inserm, U1216, Grenoble Institut Neurosciences, 38000 Grenoble, France
[d] Dipartimento di Fisica e Astronomia "Galileo Galilei", Università di Padova, via Marzolo 8, Padova 35131, Italy
[e] Padua Neuroscience Center, Università di Padova, via Orus 2, Padova 35131, Italy

Frites: A Python package for functional connectivity analysis and group-level statistics of neurophysiological data

Etienne Combrisson [1], **Ruggero Basanisi** [1], **Vinicius Lima Cordeiro** [1,2], **Robin A. A Ince** [3], and **Andrea Brovelli** [1]

1 Institut de Neurosciences de la Timone, Aix Marseille Université, UMR 7289 CNRS, 13005, Marseille, France **2** Institut de Neurosciences des Systèmes, Aix-Marseille Université, UMR 1106 Inserm, 13005, Marseille, France **3** Institute of Neuroscience and Psychology, University of Glasgow, Glasgow, UK

DOI: 10.21105/joss.03842

Software

- Review
- Repository
- Archive

Editor: Marie E. Rognes

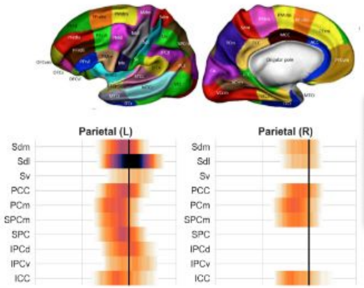
Reviewers:

- @madvn
- @travisbthomp

Summary

The field of cognitive computational neuroscience addresses open questions regarding the complex relation between cognitive functions and the dynamic coordination of neural activity over large-scale and hierarchical brain networks. State-of-the-art approaches involve the characterization of brain regions and inter-areal interactions that participate in cognitive processes (Battaglia & Brovelli, 2020). More precisely, the study of cognitive brain networks underlies linking local neural activity or interactions between brain regions to experimental variables, such as sensory stimuli or behavioral responses. The relation between the brain data and external variables might take complex forms (e.g. non-linear relationships) with strong variations across brain regions and participants. Therefore, powerful measures of information

Information theory for brain interactions



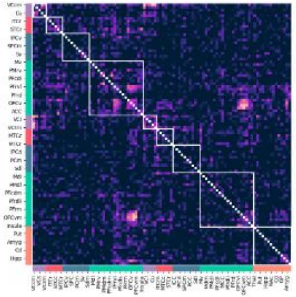
Neurophysiological data

↓

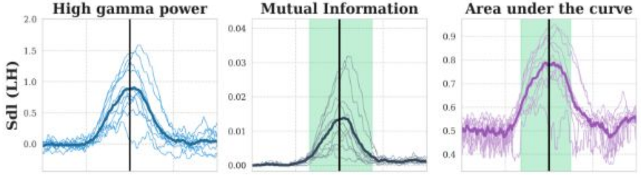
IT Framework

Local encoding

Neural interactions and broadcasting



Group-level statistical inferences



Combrisson E, Allegra M, Basanisi R, Ince RAA, Giordano B, Bastin J, Brovelli A (2022) *NeuroImage*

Typical Pipeline

Data	Dataset	Information	Statistics	Results
	`frites.dataset`	`frites.workflows`	`frites.workflows`	

Data

Brain data

- LFP, connectivity, spikes, power, TF maps etc.
  - Single / Multi subjects
  - Single / Multi sessions
  - Single / Multi brain regions

Task variable

- **Categorical variable**
  - Stimulus type
  - Experimental condition
- **Continuous variable**
  - Behavioral model (PE, surprise)
  - Reaction time

Dataset

`DatasetEphy`

Merge group data

- x = brain data
- y = task variable
- Checking data properly formatted
- Data conversion

Information

`WfMi`

Measure of effect size

- Linking the brain data to the task variable ($I(x; y)$)
- Provide a measure of effect size
  - Per / across subjects
  - Per / across sessions

Statistics

`WfStats`

Corrected p-value

- Effect significantly differ from chance?
- Correct for multiple comparisons (time, space etc. e.g. using cluster-based)
- P-value inference

Results

Effect size

- Per brain region / electrode
- Dynamic (per time point if there's a time axis)
- Per or across a population (i.e. across subjects or sessions)

P-value

- Same dimension as the effect size
- Corrected for multiple-comparisons

Cooking Frites

https://github.com/brainets/CookingFrites

EBRAINS Academy Workshop Series
Session 1 – intracranial EEG

1. **Login to the EBRAINS Collab**

   https://wiki.ebrains.eu/

2. **Connect to EBRAINS Academy iEEG Collab and Drive**

   https://wiki.ebrains.eu/bin/view/Collabs/ebrains-academy-workshop-ieeg/

   https://wiki.ebrains.eu/bin/view/Collabs/ebrains-academy-workshop-ieeg/Drive

3. **Connect to EBRAINS lab**

   https://lab.ebrains.eu/

4. **Connect to EBRAINS drive**

   https://drive.ebrains.eu/

DATASET

Human Intracranial Database

release-5

Lachaux, J.; Rheims, S.; Chatard, B.; Dupin, M.; Bertrand, O.

- Overview
- Data descriptor
- How to cite
- Get data
- Publications
- Specimen

DOI: 10.25493/FCPJ-NZ

License:
The use of this dataset requires that the user cites the associated DOI and adheres to the conditions of use that are contained in the Data Use Agreement. You may not use the dataset for commercial purposes.

Project: Human Intracranial Database (HID)

Custodians: Lachaux, J.

The Human Intracranial Database (HID) is a collection of stereotactic electroencephalography (sEEG) data in epileptic patients, performing up to eight behavioral tasks. The behavioral tasks were used as functional localizers: short and classic task paradigms designed to activate large-scale neural networks involved in language processing (LEC1 and LEC2), verbal and visuo-spatial working memory (MVEB and MVIS), visual attention (VISU), motor behavior (MOTO), high-level visual (MCSE) and auditory perception (AUDI). Furthermore, most patients were also recorded during resting state (REST) and a series of tests designed to evaluate whether specific types of actions can generate artifacts (ARFA). The sEEG data were obtained via several sEEG depth-electrodes (linear arrays with up to 20 contacts) that were implanted in each patient in a stereotactic surgery. Coordinates of the sEEG electrode contacts are provided in the individual brain space of each patient as well as in a reference brain space (MNI ICBM 152). Semantically sEEG electrode contacts were linked to brain areas of the MarsAtlas, but can be positioned on the individual anatomy for checking purposes.

Version specification:
This is the fifth release of the Human Intracranial Database. It is comprised of stereotactic electroencephalography (sEEG) data recorded in 100 epileptic patients performing behavioral tasks. The fifth release contains data from 20 new patients as compared to release-4. The data structure of this release is conform to the Brain Imaging Data Structure (BIDS) standard v1.2.0.

Study targets:
- alpha activity
- beta activity
- gamma activity
- local field potential
- working memory

view all

Behavioral protocols:
- Auditory Perception Task (Perrone-Bertolotti et al. 2012)
- Visuo-Spatial Working Memory Task (Hamamé et al. 2012)
- Instructed Moto-Coordination Task (Lachaux et al., 2020)
- Resting State Paradigm (Lachaux et al. 2020)
- Sternberg's Verbal Working Memory Task (Hamamé et al., 2012)

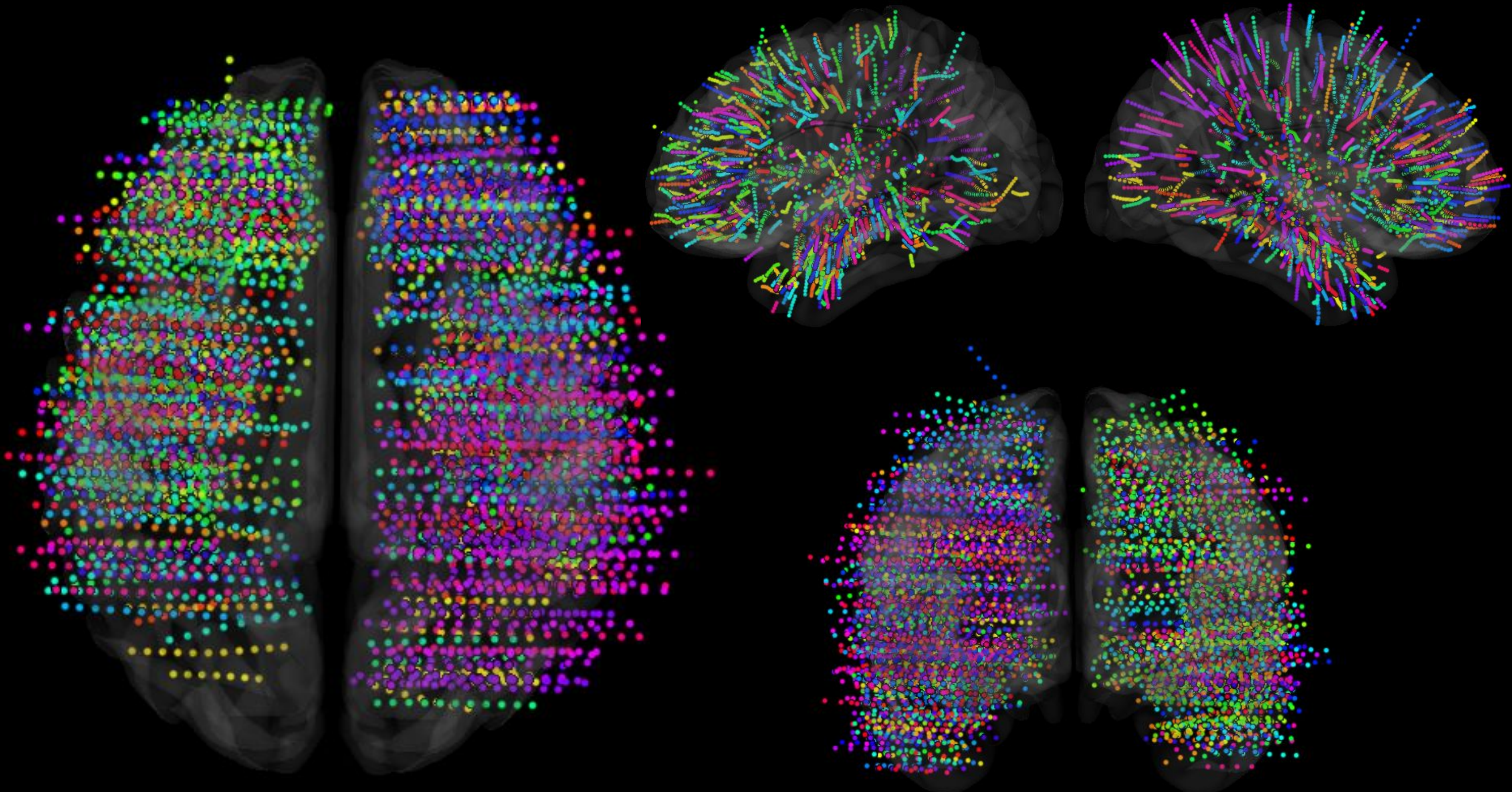
view all

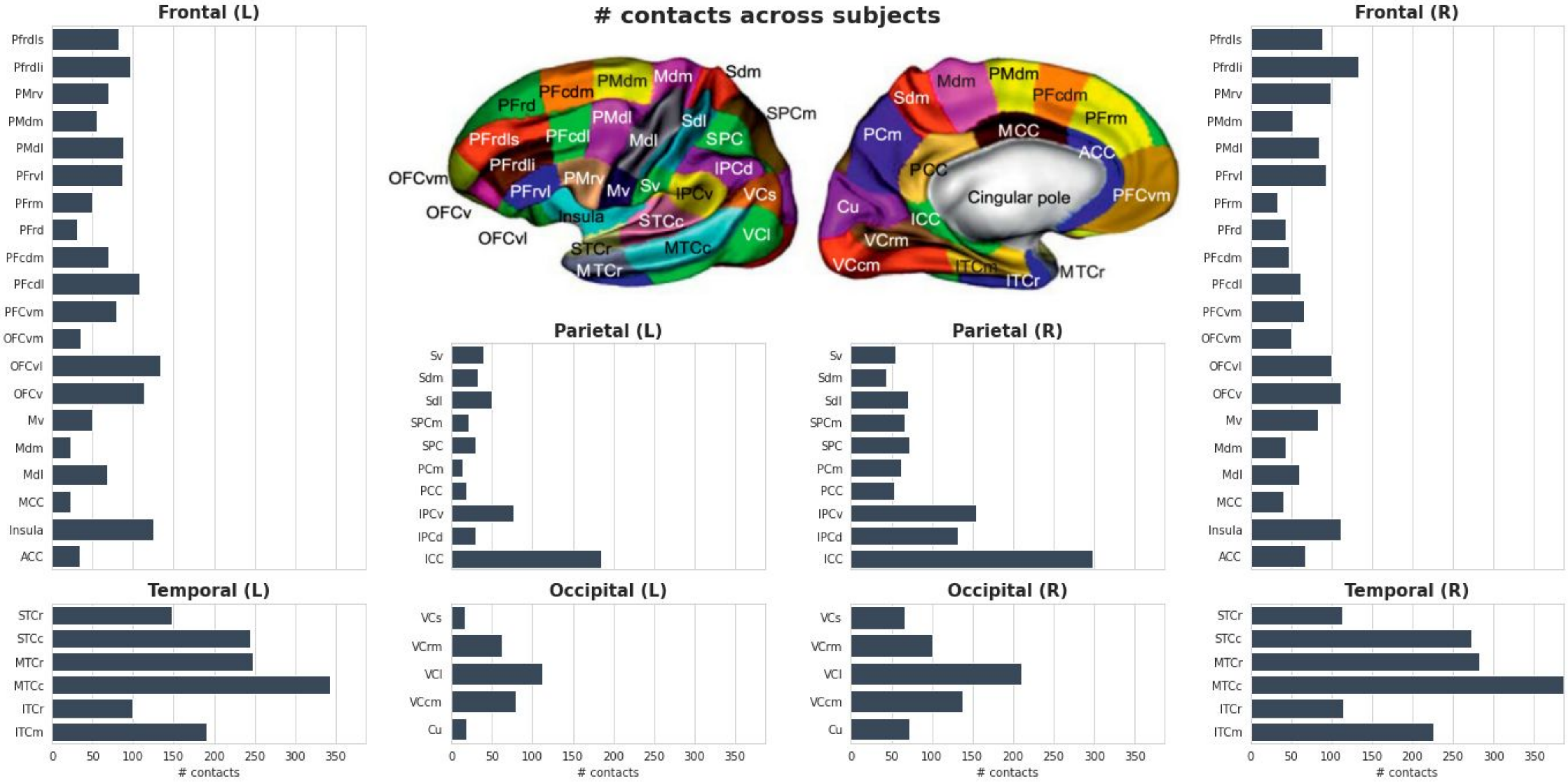
Preparation: in vivo

Experimental approach:
- electrophysiology
- behavior

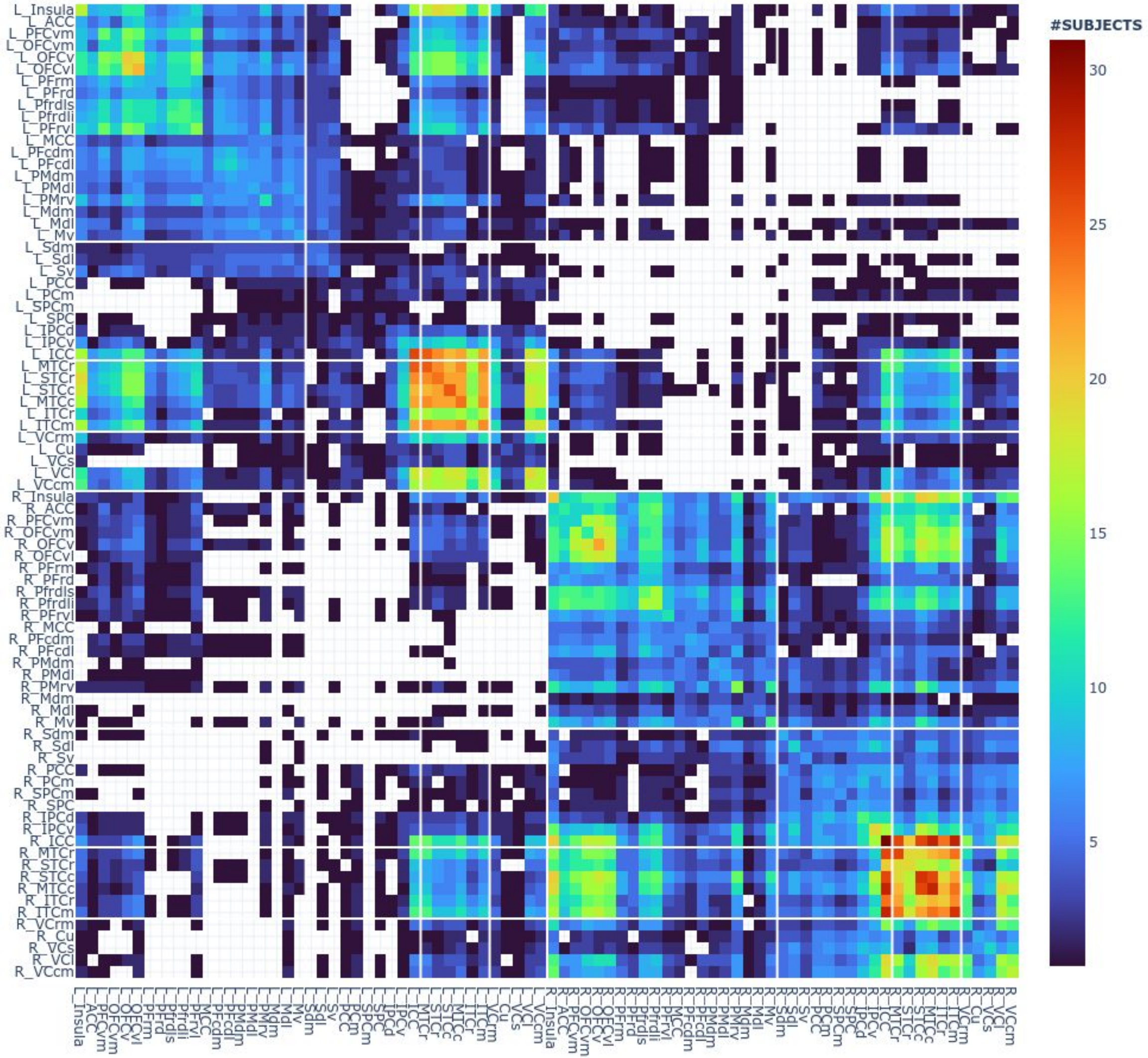
Technique:
- stereoelectroencephalography
- stereotactic surgery
- implant surgery
- magnetic resonance imaging
- transformation

Keywords:
- functional localizers





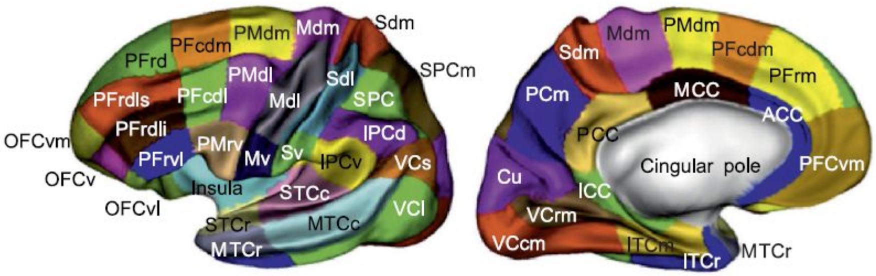
contacts across subjects
Frontal (L)
Frontal (R)
Parietal (L)
Parietal (R)
Temporal (L)
Occipital (L)
Occipital (R)
Temporal (R)
Pfrdls
Pfrdli
PMrv
PMdm
PMdl
PFrvl
PFrm
PFrd
PFcdm
PFcdl
PFCvm
OFCvm
OFCvl
OFCv
Mv
Mdm
Mdl
MCC
Insula
ACC
Sv
Sdm
Sdl
SPCm
SPC
PCm
PCC
IPCv
IPCd
ICC
STCr
STCc
MTCr
MTCc
ITCr
ITCm
VCs
VCrm
VCl
VCcm
Cu
Cingular pole
0 50 100 150 200 250 300 350
contacts



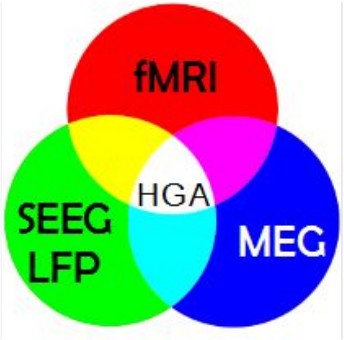
#SUBJECTS
30
25
20
15
10
5
L_Insula
L_ACC
L_PFCvm
L_OFCvm
L_OFCv
L_OFCvl
L_PFrm
L_PFrd
L_Pfrdls
L_Pfrdli
L_PFrvl
L_MCC
L_PFcdm
L_PFcdl
L_PMdm
L_PMdl
L_PMrv
L_Mdm
L_Mdl
L_Mv
L_Sdm
L_Sdl
L_Sv
L_PCC
L_PCm
L_SPCm
L_SPC
L_IPCd
L_IPCv
L_ICC
L_MTCr
L_STCr
L_STCc
L_MTCc
L_ITCr
L_ITCm
L_VCrm
L_Cu
L_VCs
L_VCl
L_VCcm
R_Insula
R_ACC
R_PFCvm
R_OFCvm
R_OFCv
R_OFCvl
R_PFrm
R_PFrd
R_Pfrdls
R_Pfrdli
R_PFrvl
R_MCC
R_PFcdm
R_PFcdl
R_PMdm
R_PMdl
R_PMrv
R_Mdm
R_Mdl
R_Mv
R_Sdm
R_Sdl
R_Sv
R_PCC
R_PCm
R_SPCm
R_SPC
R_IPCd
R_IPCv
R_ICC
R_MTCr
R_STCr
R_STCc
R_MTCc
R_ITCr
R_ITCm
R_VCrm
R_Cu
R_VCs
R_VCl
R_VCcm

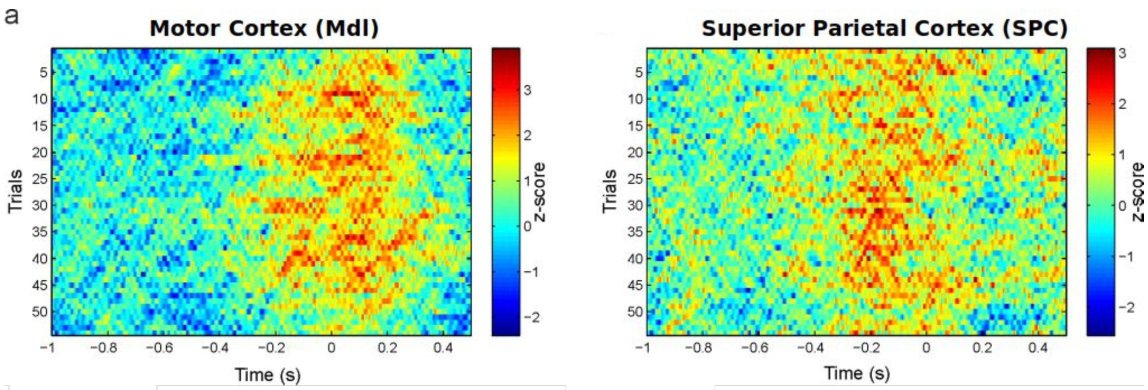
Single-trial and Atlas-based High-Gamma Activity

MarsAtlas



High-Gamma Activity (60-120Hz)





Brovelli et al (2015; 2017) *Journal of Neuroscience*

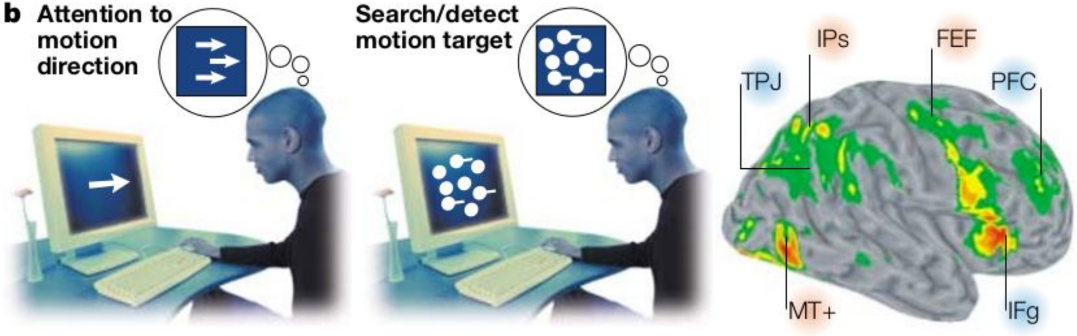
Visual Search

NATURE REVIEWS | NEUROSCIENCE VOLUME 3 | MARCH 2002 | 201

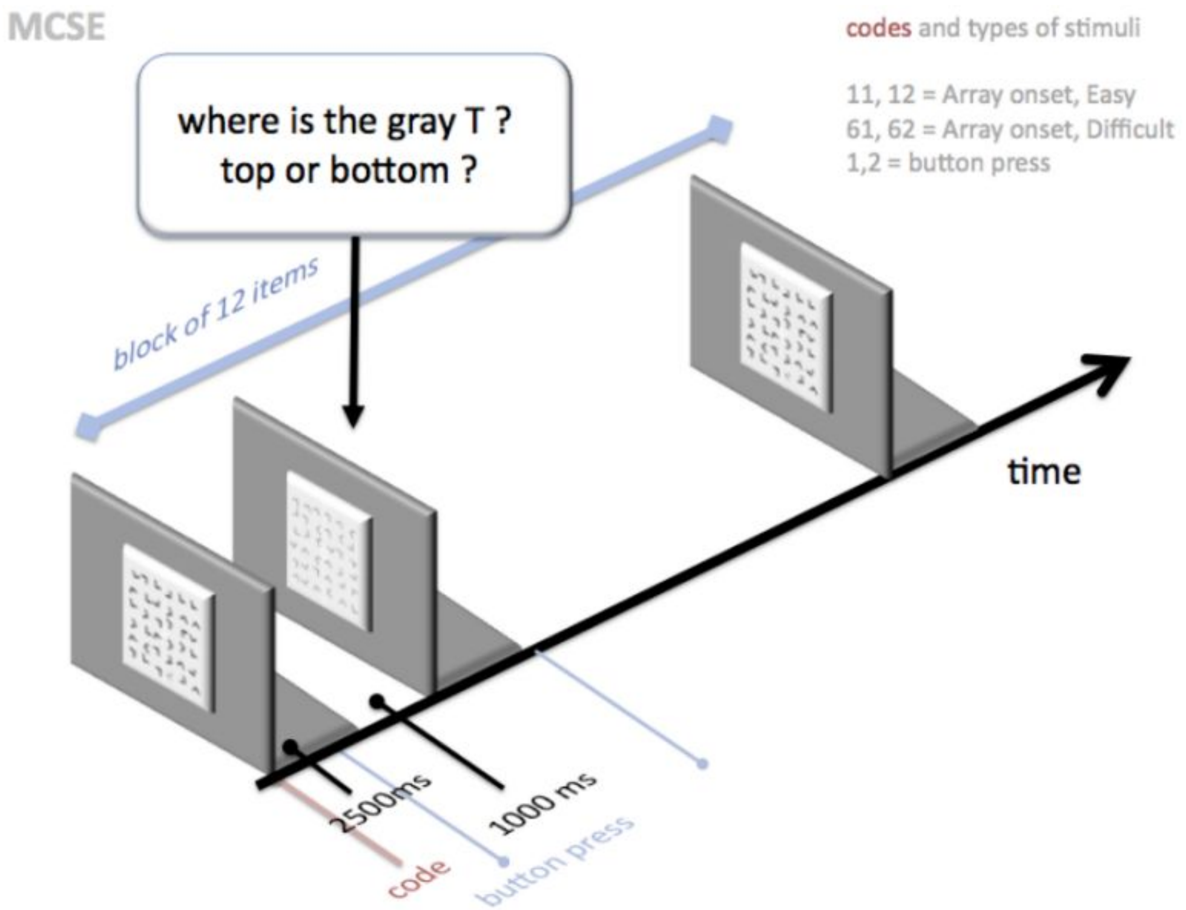
CONTROL OF GOAL-DIRECTED AND STIMULUS-DRIVEN ATTENTION IN THE BRAIN

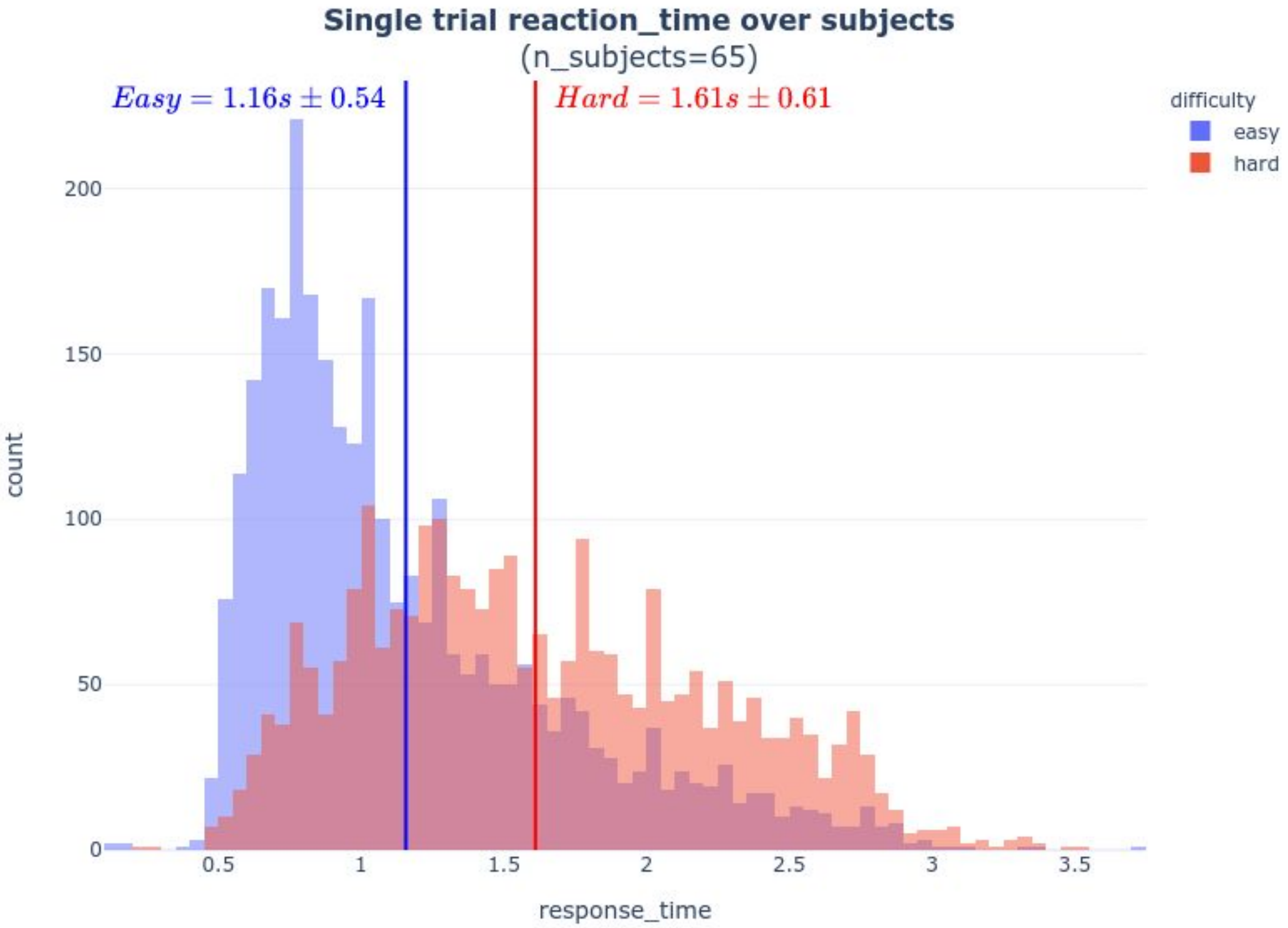
Maurizio Corbetta and Gordon L. Shulman

We review evidence for partially segregated networks of brain areas that carry out different attentional functions. One system, which includes parts of the intraparietal cortex and superior frontal cortex, is involved in preparing and applying goal-directed (top-down) selection for stimuli and responses. This system is also modulated by the detection of stimuli. The other system, which includes the temporoparietal cortex and inferior frontal cortex, and is largely lateralized to the right hemisphere, is not involved in top-down selection. Instead, this system is specialized for the detection of behaviourally relevant stimuli, particularly when they are salient or unexpected. This ventral frontoparietal network works as a 'circuit breaker' for the dorsal system, directing attention to salient events. Both attentional systems interact during normal vision, and both are disrupted in unilateral spatial neglect.

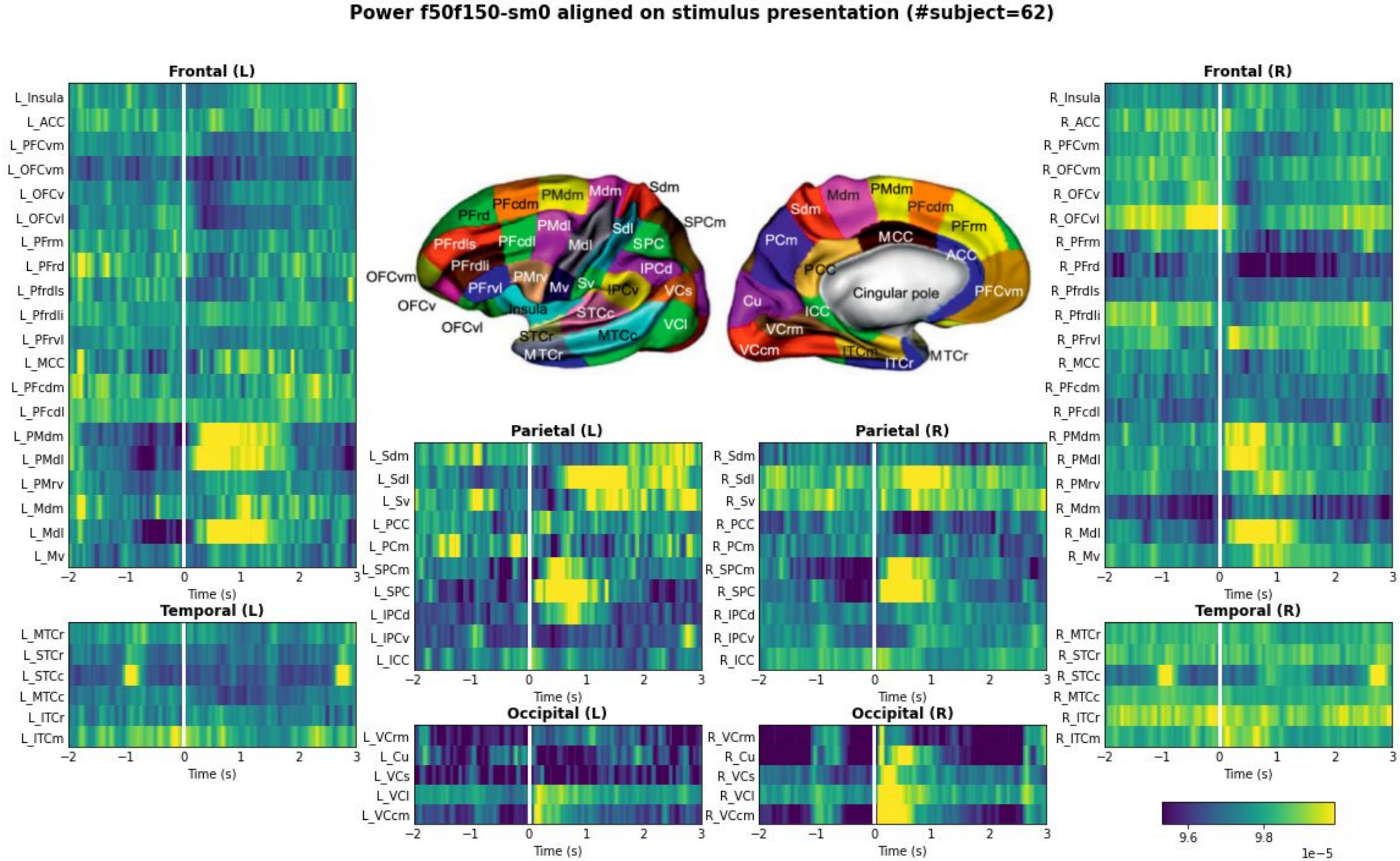


Human iEEG data - Visual search

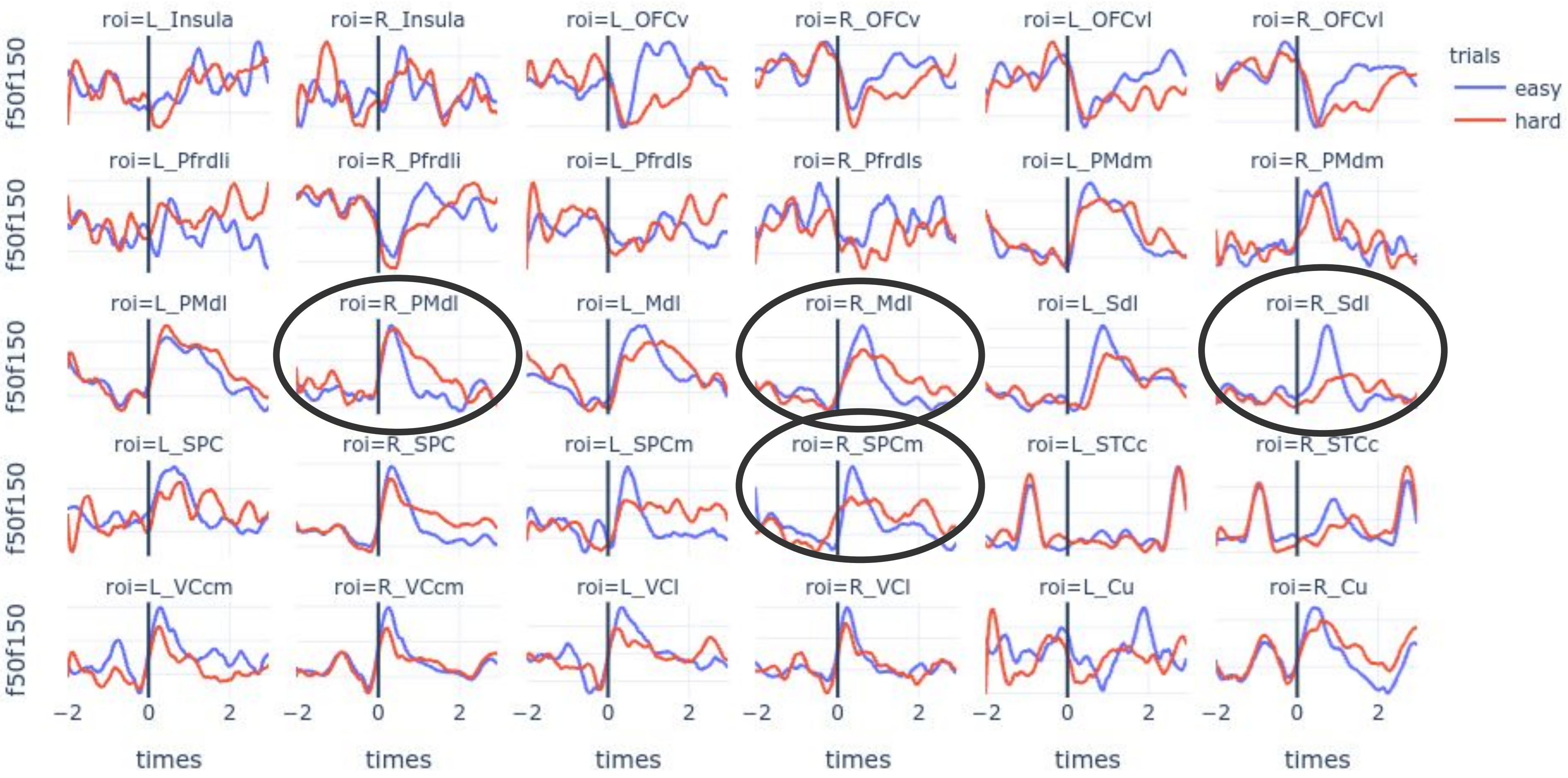




Single trial reaction_time over subjects
(n_subjects=65)
$Easy = 1.16s \pm 0.54$
$Hard = 1.61s \pm 0.61$
difficulty
easy
hard
count
200
150
100
50
0
0.5
1
1.5
2
2.5
3
3.5
response_time

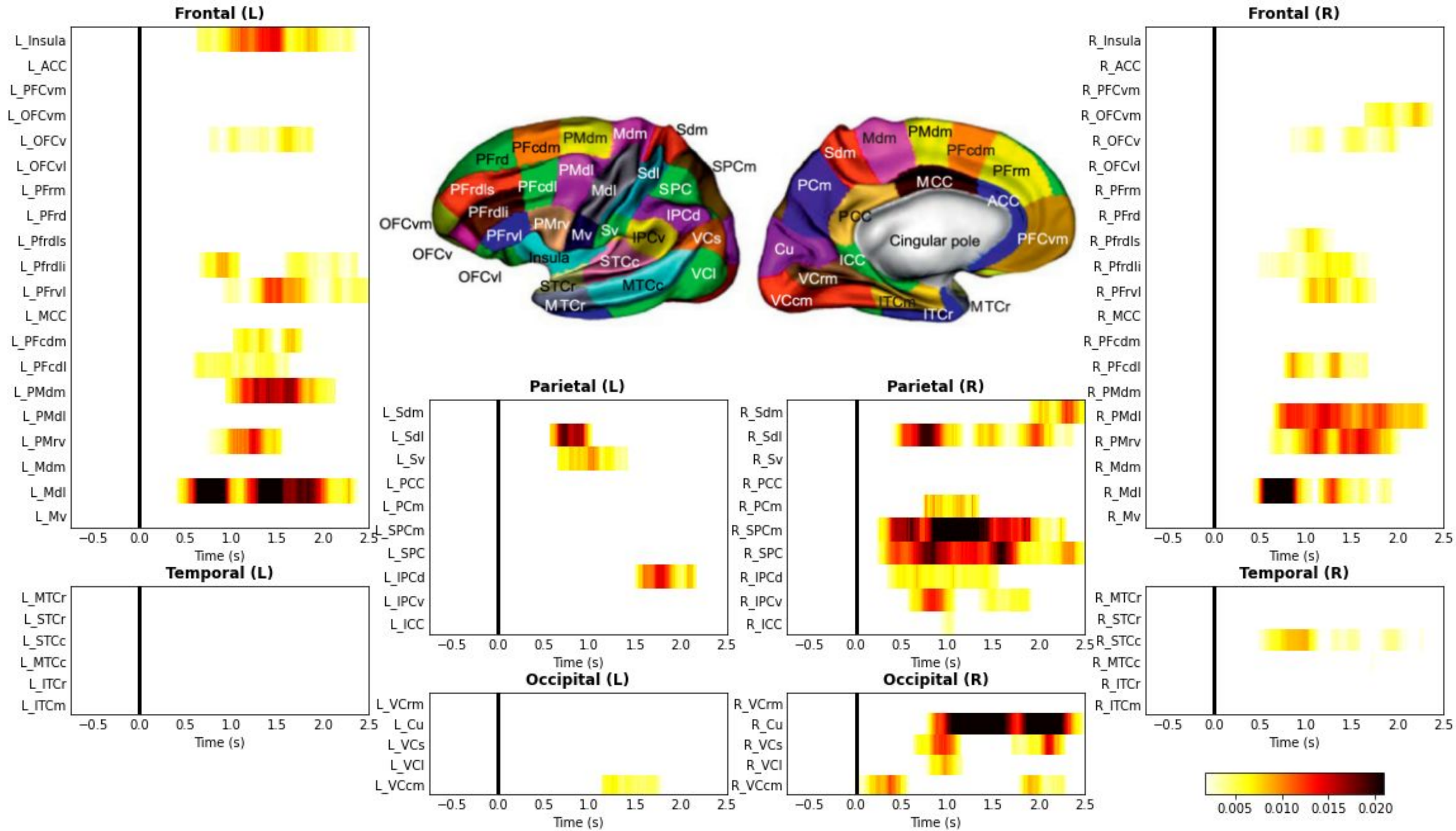


Power f50f150-sm0 aligned on stimulus presentation (#subject=62)
Frontal (L)
L_Insula
L_ACC
L_PFCvm
L_OFCvm
L_OFCv
L_OFCvl
L_PFrm
L_PFrd
L_Pfrdls
L_Pfrdli
L_PFrvl
L_MCC
L_PFcdm
L_PFcdl
L_PMdm
L_PMdl
L_PMrv
L_Mdm
L_Mdl
L_Mv
Time (s)
Frontal (R)
R_Insula
R_ACC
R_PFCvm
R_OFCvm
R_OFCv
R_OFCvl
R_PFrm
R_PFrd
R_Pfrdls
R_Pfrdli
R_PFrvl
R_MCC
R_PFcdm
R_PFcdl
R_PMdm
R_PMdl
R_PMrv
R_Mdm
R_Mdl
R_Mv
Temporal (L)
L_MTCr
L_STCr
L_STCc
L_MTCc
L_ITCr
L_ITCm
Temporal (R)
R_MTCr
R_STCr
R_STCc
R_MTCc
R_ITCr
R_ITCm
Parietal (L)
L_Sdm
L_Sdl
L_Sv
L_PCC
L_PCm
L_SPCm
L_SPC
L_IPCd
L_IPCv
L_ICC
Parietal (R)
R_Sdm
R_Sdl
R_Sv
R_PCC
R_PCm
R_SPCm
R_SPC
R_IPCd
R_IPCv
R_ICC
Occipital (L)
L_VCrm
L_Cu
L_VCs
L_VCl
L_VCcm
Occipital (R)
R_VCrm
R_Cu
R_VCs
R_VCl
R_VCcm
−2 −1 0 1 2 3
9.6 9.8 1e−5
PFrd PFcdm PMdm Mdm Sdm SPCm PFrdls PFcdl PMdl Mdl Sdl SPC PFrdli PMrv IPCd OFCvm PFrvl Mv Sv IPCv VCs OFCv Insula STCc VCl OFCvl STCr MTCc MTCr
Sdm Mdm PMdm PFcdm PFrm PCm MCC ACC PCC Cingular pole PFCvm Cu ICC VCrm VCcm ITCm ITCr MTCr



roi=L_Insula
roi=R_Insula
roi=L_OFCv
roi=R_OFCv
roi=L_OFCvl
roi=R_OFCvl
roi=L_Pfrdli
roi=R_Pfrdli
roi=L_Pfrdls
roi=R_Pfrdls
roi=L_PMdm
roi=R_PMdm
roi=L_PMdl
roi=R_PMdl
roi=L_Mdl
roi=R_Mdl
roi=L_Sdl
roi=R_Sdl
roi=L_SPC
roi=R_SPC
roi=L_SPCm
roi=R_SPCm
roi=L_STCc
roi=R_STCc
roi=L_VCcm
roi=R_VCcm
roi=L_VCl
roi=R_VCl
roi=L_Cu
roi=R_Cu
f50f150
times
trials
easy
hard

I(gamma; Easy vs. Hard) - data aligned on stimulus presentation



Task-related Dynamic Functional Connectivity DCF (easy vs hard conditions)